The Dissertation Committee for Tobin Knowles McKearin Certifies that this is the approved version of the following dissertation:

ESSAYS ON THE EFFECTS OF GOVERNMENT INTERVENTION IN TEXAS' ELECTRICITY MARKET AND THE HEALTH INSURANCE MARKETS IN MISSOURI AND OKLAHOMA

Committee:

Michael Geruso, Supervisor

Jason Abrevaya

Gerald S. Oettinger

Jay Zarnikau

Nathan N. Wozny

ESSAYS ON THE EFFECTS OF GOVERNMENT INTERVENTION IN TEXAS' ELECTRICITY MARKET AND THE HEALTH INSURANCE MARKETS IN MISSOURI AND OKLAHOMA

by

Tobin Knowles McKearin, B.S.; M.A.; M.S. Inf. Tech. Mgt.; M.S. Econ

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

The University of Texas at Austin

December 2015

Acknowledgements

I want to acknowledge the aid and supervision of my Adviser, Michael Geruso. He has spent countless hours selflessly helping me ensure I complete a dissertation worthy of a Ph.D. from the University of Texas. I also want to acknowledge my entire dissertation committee. Without their help and guidance, I know I would not be where I am today. I hope to bring respect to the University of Texas' Department of Economics through future work and hope to be counted as one of the department's success stories.

Most importantly, I want to acknowledge my wife, Angie McKearin, who has taken on all the duties of the home and sacrificed probably more than I have in the past three plus years in order to give me the best chance of succeeding. Without her support and dedication to our children and my studies, to our home and our friends, and ability to put up with my lack of presence at the house to help raise our two boys, especially during the first year but really in all three years, I would not have succeeded. Thank you, Angie, I realize how much I owe you for this and hope I can somehow balance this debt in the coming years. I also want to apologize to our oldest son, Linden. I am sorry I spent almost a year and a half away from you. I hope to make that up to you in our future!

Lastly, I'd like to acknowledge the help and friendship from some of my classmates. Without Carlos Herrera's advice and help, I could not have completed this dissertation—thank you for everything. Without your skills, demeanor, and willingness to help at any time throughout the three plus years I know I would not have made it to this point. Additionally, Randeep Kaur, Luke Rodgers, Collin Hansen, Mario Vega, and Hassan Khosroshahi were always there to lend an ear and offer advice on how to proceed—thanks to all of you.

ESSAYS ON THE EFFECTS OF GOVERNMENT INTERVENTION IN TEXAS' ELECTRICITY MARKET AND THE HEALTH INSURANCE MARKETS IN MISSOURI AND OKLAHOMA

Tobin Knowles McKearin, Ph.D.

The University of Texas at Austin, 2015

Supervisor: Michael Geruso

This public economics dissertation examines the effects resulting from government intervention in the electricity and health insurance markets. The first chapter analyzes the impact on residential electricity prices by studying a once regulated market in which government regulators withdrew from in hopes of allowing a free and competitive market to flourish. The second chapter analyzes the resulting effects on employment and other forms of health insurance that occur when the government tightens the income limits to qualify for Medicaid. The third and final chapter studies employment, health insurance, health, and emergency room usage effects when the government gives subsidies to employers providing health insurance to their employees.

Table of Contents

List of Tables ix

List of Figures xi

Chapter 1: The Effect on Prices of Deregulation in Texas' Electricity Market.......1

1. Introduction..1
2. Background..6
3. Relevant Literature..11
4. Data..16
5. Main Empirical Strategy and Main Results..19
    - 5.1. Main Empirical Strategy..19
    - 5.2. Main Empirical Results...21
6. Model..24
    - 6.1. Pricing Based on Marginal versus Average Costs........................24
    - 6.2. Bilateral Contracts, Day-Ahead Market, Real-Time Market........28
7. Empirical Strategy and Results Evaluating the Role of Natural Gas........30
    - 7.1. Empirical Strategy...30
    - 7.2. Empirical Results Evaluating the Role of Natural Gas..................33
8. Robustness Checks..35
9. Conclusion..40

Chapter 2: Labor Market and Health Insurance Effects of Missouri's Medicaid Contraction..54

1. Introduction..54
2. Missouri's Health Care Reform..59
3. Model..63
4. Data and Empirical Strategy..65
    - 4.1. Data...65
    - 4.2. Empirical Strategy...68
5. Empirical Results...73
    - 5.1. Effects on Health Insurance...73

5.2. Effects on Labor Supply 75

6. Robustness Checks and Falsification Tests 81

6.1. Robustness Check Using Border States 81

6.2. Robustness Check Using Different Education Levels 82

6.3. Robustness Check Using Different Income Levels 84

6.4. Additional Crowd-out Estimates..87

6.5. State Falsification Tests 88

7. Conclusion 92

Chapter 3: Effects of OK Subsidies to Employers Offering Health Insurance....111

1. Introduction..111

2. Related Literature...116

3. Insure Oklahoma 120

4. Model 126

5. Data and Empirical Strategy 128

5.1 Data 128

5.2 Empirical Strategy 130

6. Preliminary Results 132

6.1. Effects on Health Insurance 132

6.2. Effects on Self-Reported Health, Emergency Room Usage, and Employment 137

7. Plans for Future Implementation (after dissertation is complete)..........140

Appendix to Chapter 1 155

A.1. Background (Detailed)...155

A.2. Economic Theory for Regulation and Deregulation 158

A.3. Why the Price of Natural Gas Affects the Controls Differently 162

A.4. Non-Weighted Results, Support for Quantity being Exogenous, Balanced Panel Set...166

A.4.1. Non-Weighted Regression Results 166

A.4.2. Quantity is Arguably Exogenous 169

A.4.3. Using a Balanced Panel Data Set...170

A.5. Allowing the Effect of Deregulation to Vary by Year 171

References 183

For Chapter 1 183

For Chapter 2 187

For Chapter 3 190

List of Tables

Table 1.1: Summary Statistics 49

Table 1.2: Dependent Variable: Average Price ($/1,000 kWh) 50

Table 1.3: Dependent Variable: Average Price ($/1,000 kWh) 51

Table 1.4: Dependent Variable: Average Price ($/1,000 kWh) 52

Table 1.5: Dependent Variable: Average Price ($/1,000 kWh) 53

Table 2.1: Missouri's Medicaid Income Changes 101

Table 2.2: 2005 Federal Poverty Levels 101

Table 2.3: Summary Statistics Using CPS Data...102

Table 2.4: Summary Statistics Using ACS Data 103

Table 2.5: CPS DDD Results – Adults with a High School Diploma or Less103

Table 2.6: ACS DDD Results – Adults with a High School Diploma or Less104

Table 2.7: Crowd-out Estimate...104

Table 2.8: CPS and ACS Regressions Results Using Border States.............105

Table 2.9: Robustness Check Using CPS Data: Different Education Levels106

Table 2.10: Robustness Check Using ACS Data: Different Education Levels106

Table 2.11: Robustness Check Narrowing In On Income Using the CPS 107

Table 2.12: Robustness Check Narrowing In On Income Using the ACS....108

Table 2.13: Checking If Missouri Had an Income Distribution Change......109

Table 2.14: Additional Crowd-out Estimates...110

Table 3.1: Summary Statistics 153

Table 3.2: CPS DD Regressions Results 154

Table A.1: Dependent Variable: Average Price ($/1,000 kWh)....................177

Table A.2: Dependent Variable: Average Price ($/1,000 kWh)....................178

Table A.3: Dependent Variable: ln (total sales) 179

Table A.4: Dependent Variable: Average Price ($/1,000 kWh)....................180

Table A.5: Dependent Variable: Average Price ($/1,000 kWh)....................181

Table A.6: Dependent Variable: Average Price ($/1,000 kWh)....................182

List of Figures

Figure 1.1: Firm and Region Relationship 43

Figure 1.2: Deregulated Regions in Texas 43

Figure 1.3: Average Price of Deregulated and Controls Regions....................44

Figure 1.4: Average Cost vs. Marginal Cost in the Electricity Market 45

Figure 1.5: Price of Fuels used to Generate Electricity 45

Figure 1.6: Percentage of Fuel Used to Generate Electricity in Texas 46

Figure 1.7: Price of (Deregulated – Control Firms) and the Price of Natural Gas 46

Figure 1.8: Average Price of Deregulated Firms, Municipalities, and Investor Owned Utilities 47

Figure 1.9: Average Price of 5 Incumbents vs. 4 Regulated Investor Owned Utilities 47

Figure 1.10: Average Price of 5 Incumbents, 5 Biggest Municipalities, 5 Biggest Controls...48

Figure 1.11: Average Price of 5 Incumbents and 3 Largest Cooperatives 48

Figure 1.12: Average Price of 5 Incumbents, 4 Regulated Investor Owned Utilities, and the Price of Natural Gas 49

Figure 2.1: Medicaid Enrollment in Missouri..95

Figure 2.2: Model for Medicaid Contraction 95

Figure 2.3: Public Health Insurance 96

Figure 2.4: Employer Sponsored Health Insurance 96

Figure 2.5: Employed...97

Figure 2.6: CPS State Falsifications 98

Figure 2.7: ACS State Falsifications..100
Figure 3.1: Annual Enrollment in SoonerCare and Insure Oklahoma 148
Figure 3.2: Monthly Enrollment in Insure Oklahoma 148
Figure 3.3: Labor Demand and Supply 149
Figure 3.4: Employer Sponsored Health Insurance 149
Figure 3.5: Private Health Insurance..150
Figure 3.6: Public Health Insurance 150
Figure 3.7: Employed..151
Figure 3.8: Self-Reported Health Status...151
Figure 3.9: Emergency Room Visits..152
Figure A.1: NERC Regions in North America..173
Figure A.2: Independent System Operators in Texas 173
Figure A.3: FERC division of power markets..174
Figure A.4: Monopoly vs Competitive Market 174
Figure A.5: Average Price of Deregulated Regions vs Controls...................175
Figure A.6: Price of (Deregulated– Controls Firms) and the Price of Natural Gas 175
Figure A.7: Quantity Sold in the Deregulated and Control Regions 176

Chapter 1: The Effect on Prices of Deregulation in Texas' Electricity Market

1. Introduction

Does deregulation decrease prices? Specifically, does deregulation of the electricity market decrease electricity prices to residential consumers? In the past two decades, deregulation has become a popular topic among policy makers in cities, states, and countries. Proponents of deregulation argue lower prices, better service, increased options, more jobs, more investment, and increased generation from alternative fuels are advantages to deregulating the electricity market.[1] Critics argue these advantages will not occur, that consumers in deregulated regions do not benefit, that deregulated areas should re-regulate their electricity markets, and regulated markets should remain regulated.[2]

Economic theory provides no definitive answer concerning deregulation's effect on prices. The final price consumers pay is affected by the number of firms entering the market, the market power possessed by one or a group of firms, effects caused by removing a price ceiling, and the differential impact that input costs have on deregulated markets. Due to the ambiguity of price changes following deregulation, an empirical analysis can help determine deregulation's effect on prices. Supporting the ambiguity from the theoretical perspective, prior literature studying deregulation's effect on prices

[1] See Woo and Zarnikau (2009), TCAP (2012), Roe et al. (2001).
[2] TCAP (2012)

offers no consensus as to whether the critics or proponents are correct.[3] This paper informs that debate.

Electricity markets in the United States have historically been regulated monopolies controlling all four aspects of electricity: generation, transmission, distribution, and retail customer service. Some electricity markets in Texas followed this same basic design, but had the retail customer service portion of their market deregulated in 2002.[4] The electricity market in Texas provides a unique opportunity to examine deregulation's effect on the prices residential consumers pay, to determine if critics or proponents are correct, and to educate policy makers in their decision to deregulate or not.

This paper investigates the question by studying the prices charged to residential consumers before and after deregulation. In 2002, the electricity markets in some regions of the state became deregulated while other regions experienced no changes. Taking advantage of this within-state variation that occurred at the regional level by using a difference-in-difference regression, this paper provides the first econometric analysis of deregulation's effect on residential prices in Texas' electricity market.

The estimates in this paper lead to a causal interpretation that deregulation of the electricity market leads to higher prices in this context.[5] The average residential

[3] See: Swadley and Yucel (2011), Rose (2004), Whitworth and Zarnikau (2006), Joskow (2006), and Axelrod et al. (2006) for differing conclusions.
[4] While Texas followed the same basic design, it has some differences explained in the background section.
[5] As will be explained later, this increase is likely related to the increasing price of natural gas. If the price of natural gas had decreased instead of increasing at the same time as deregulation occurred, results might be opposite to what I report here.

customer in the deregulated regions paid approximately $850 more from 2002 to 2006 and $1,700 more from 2007-2012 due to deregulation. A 95% confidence interval shows the average customer paid $741 to $993 extra for the first 5 years. Difference-in-difference plots that allow the effect of the 2002 deregulation to vary by year show no impacts prior to 2002, providing evidence supporting the parallel trends identifying assumption. This paper confirms the robustness of these findings by estimating multiple difference-in-difference specifications that isolate subsets of the identifying variation. I obtain similar estimates when isolating variation by using subsets of similar size regions and similar business model makeup, reducing concerns that size or business structure are biasing my results.

The second part of this paper investigates how an important determinant of the higher prices following deregulation is due to how input costs pass through differentially in the deregulated and regulated markets. It addresses the question: What is the differential impact resulting from input costs on the price residential consumers face in the deregulated regions versus the other regions? By using the same difference-in-difference methodology described above but interacting the cost of natural gas with the independent variables, this paper shows that, due to deregulation, a $1 increase per million British Thermal Units (MBTU) in the cost of natural gas leads to a $4.84 increase per month to the average residential customer in the deregulated regions.[6,7,8] In Texas,

---

[6] The mean of the price of natural gas from 2002 to 2012 was $5.43/MBTU and the mean monthly price to the average residential consumer was $96.43.

[7] 1kwh = 3,412 BTUs. Therefore, a $1/MBTU increase equates to a $3.41/1,000 kwh increase ($1/MBTU x 1MBTU/293.08 kwh x 1,000). Steam driven systems (accounting for 72% of US electricity production)

natural gas is the primary fuel used to produce electricity, accounting for 45%-51% of the state's electricity generation (EIA, 2015). This, along with the fact that it is the most costly of the fuels used to produce electricity, makes the price of it the key input making up the marginal cost of electricity.

Electricity market deregulation throughout the country has had mixed success.[9] Texas is often touted as the most successfully restructured electricity market in North America (DEFG, 2012 and Klump, 2015). Countries, states, and regions are trying to determine if they should deregulate their electricity markets or keep them regulated. They are primarily basing their final decision on their observations, evaluations, and outcomes of deregulated states. Even some states that deregulated their electricity markets are analyzing theirs and others' electricity markets and are considering re-regulating or changing some of the rules of their deregulated electricity market. To date, 27 states have not attempted deregulation and 7 have suspended their deregulation of the electricity market and re-regulated it.[10] Not only are states trying to determine if they should deregulate, but regions in Texas unaffected by the 2002 deregulation are also trying to determine how they should proceed. By studying the "successful" deregulation

---

are 30%-40% efficient; gas turbines have roughly the same efficiency; combined cycle are 40%-60% efficient; combined heat and power are 70%-85% efficient; and transmission lines are 90% efficient (Webber, 2015). Assuming 40% efficiency at the source of electricity generation, by the time the household receives the electricity it has been reduced by 36% of what the generation company started with (40% * 90% for the transmission lines). $3.41 divided by 0.36 = $9.48. Thus, almost half of the price increase of natural gas is passed on to the consumer.

[8] As shown in Appendix Section A.4.2, there is no quantity response to a change in price; therefore, I cannot reject a price elasticity of zero. Such an inelastic response is supported by prior studies (see Nakajima and Hamori, 2010, and their references).

[9] See Swadley and Yucel (2011) and Su (2015).

[10] See http://www.eia.gov/electricity/policies/restructuring/restructure_elect.html.

of Texas and determining deregulation's effect on prices, I can show how one of the more successfully deregulated markets has fared to help policy makers make an educated decision moving forward.

The findings in this paper do not support deregulation for entities (be it countries, states, regions, or others) who place a high value on the price residential consumers pay.[11] The findings further show that the input fuel costs must be below levels not observed throughout most of the studied interval in order for deregulation to have had the negative effect on prices proponents argued would happen. The results from this paper show electricity markets in Texas do not follow popular intuition that moving to a deregulated market necessarily results in lower prices.

The way a state deregulates their electricity market affects the success or failure of the deregulation. Many papers provide research, analysis, and proposals for different ways to deregulate the electricity market of a state.[12] While the way a state deregulates is clearly important, this paper does not attempt to study how a state should go about deregulating their electricity market. I study Texas to determine if deregulation affects prices and to see if consumers benefited in a state that is mainly considered to have successfully deregulated in hopes of providing policy makers with more information when deciding on whether to proceed with deregulation.

[11] I specify this because I want to clarify that I am not directly evaluating the economic efficiency (is deadweight loss minimized), though I do discuss this in the appendix.
[12] See Griffin and Puller (2005), Hortacsu et al (2014), Puller and West (2013), and their references for examples.

The paper proceeds as follows. Section 2 gives the relevant background. Section 3 summarizes the most relevant literature. Section 4 explains the data used. Section 5 presents the main empirical strategy and results detailing deregulation's effect on prices. Section 6 provides a model and explanation of how input costs affect the deregulated and control regions differently. Section 7 empirically evaluates the differential impact of input costs. Section 8 provides robustness checks. Section 9 concludes.

2. Background

In this section, I provide the minimum necessary background information to understand the paper. For a more detailed background and granular explanation of deregulation in the United States and in Texas please refer to Appendix Section A.1. For the interested reader, Appendix Section A.2. provides a synopsis of the economic theory for regulation and deregulation.

The deregulation studied in this paper occurred on January 1, 2002. Senate Bill 7, passed in 1999, required five regions in Texas, which account for approximately 60% of Texas' residential customers, to open the retail portion of their electricity market to competition by 2002 (EIA, 2015 and AECT, 2014). Retail customer service entails the interface with the end-user and providing hookup, metering, and billing services (PUC, 1997). Prior to 2002, nine regions, each served by a vertically integrated investor owned utility, were regulated by the Public Utility Commission of Texas (hereafter referred to as the state regulator). Prior to and after 2002, approximately 150 other regions, either municipalities or cooperatives, were not regulated by the state regulator but were overseen by some type of governing board (e.g. city council). The governing board of these regions was/is not a typical regulatory authority like the state regulator. Rather, they acted much like a board of directors does for a typical competitive firm—they set goals and objectives for the electric company to satisfy. Prior to 2002, every firm, be it an investor owned utility, municipality, or a cooperative was the only company providing electricity service in their region and thus each firm also represented a region in Texas.

Senate Bill 7 allowed new firms (as well as the incumbent firm) to buy electricity from electric generating facilities or owners of electricity and sell it to industrial, commercial, and residential customers in the deregulated regions (TCAP, 2012). Therefore, the January 2002 deregulation refers to deregulating the electricity retail customer service by opening it to competition and it happened in five regions in Texas served by five investor owned utilities. The 150 (approximately) municipalities and cooperatives and the other 4 investor owned utilities not deregulated by Senate Bill 7 maintained their same status and makeup after 2002. Following 2002, these firms were/are still the only providers of electricity in their regions; therefore, each of these firms still represented/represent specific geographic regions. The five investor owned utilities deregulated by Senate Bill 7 now had multiple firms operating in their regions and also expanded their businesses into other regions; therefore, the five incumbents no longer represented/represent specific geographic regions.

Figure 1.1 depicts the firm/region relationship and is critical, for calculating standard errors, to the difference-in-difference specification used later in this paper. In this figure, each shape (ovals and rectangles) represents a region. The information to the left of the vertical line labeled 2002 depicts the market prior to 2002. The information to the right of this line depicts the market from 2002 on. Prior to 2002, there is one firm in each of the five regions that will be deregulated. There is also one firm in each of the regions that were not deregulated by Senate Bill 7. Four regions are shown but in actuality there are almost 155 regions not deregulated. After 2002, the firms not affected by Senate Bill 7 maintain their same status--each region is still operated by the same firm. After 2002, the regions deregulated by Senate Bill 7 now have multiple firms--they have their incumbent firm, existing firms from the other deregulated regions, and new firms who were not in Texas' market prior to 2002.

From now on, I refer to the five regions Senate Bill 7 deregulated as the deregulated group and the others (approximately 155 regions) as the control group. The municipalities and cooperatives that were not affected have the choice to "opt-in" to competition but must remain competitive once making this choice. To date, only one region, Nueces Electric Cooperative, has opted-in (PUC, 2014). Due to this endogeneity issue with Nueces Electric Cooperative, I eliminate them from the data in my main regressions.[13] Further, a cooperative, municipality, or regulated investor owned utility is able to compete and offer electrical service in a deregulated region. However, if they do this, they must deregulate their region and allow competitors to enter their region. With the exception of Nueces, no one has proceeded down this road.

[13] Regression results with Nueces included are very similar and can be provided upon request.

After the passing of Senate Bill 7, in 1999, the firm in the region that would become deregulated in 2002 began restructuring (there was a different firm in each region for a total of five firms in five regions). They separated their vertically integrated utility into three sections to allow for a smoother transition in 2002; generation, transmission and distribution, and retail customer service. Electric generation in Texas was deregulated in 1995 has not significantly changed its structure since the 1995 deregulation and is thus unaffected by the 2002 deregulation.

I do not study the deregulation of electricity generation in this paper. I study only the separable retail market. The transmission and distribution portion remained regulated and became the regulated Transmission and Distribution Service Provider for their region. The retail customer service portion, the portion deregulated in 2002, became the affiliated retail electric provider (hereafter referred to as the incumbent). Initially, all customers in the area that became deregulated were assigned to the incumbent in their respective region (Horatscu et al., 2012). Figure 1.2 depicts the five service areas of the transmission and distribution service provider that became deregulated in 2002. The shaded regions represent the regions that were deregulated by Senate Bill 7.

It is plausible that the choice of the deregulated regions is exogenous to the price residential consumers pay for their electricity. One plausible reason is that the policy was set in 1999 to deregulate the regions in 2002, thus the Texas legislators were likely not reacting to some event that would affect demand or supply in 2002. Another reason is that only five of the nine regions regulated by the state regulator were within the jurisdiction of the Texas state legislature to deregulate. These five regions were completely engulfed within the state of Texas and thus the Texas legislation had complete authority over them. In contrast, the four regions regulated by the state regulator but not deregulated by Senate Bill 7 were part of Texas' market and other bordering states' markets; therefore, Texas did not have the authority to deregulate those markets. While these two reasons help support the assumption that deregulation was exogenous with respect to unobservable determinants of consumer pricing, the best evidence I can offer is to verify that there was no difference in the pricing trends of the treated and control groups during the period before deregulation. In the empirical analysis section, I present evidence showing that the prices of the deregulated firms and control firms followed the same trend prior to deregulation.

From 2002-2006, Texas went through a transitional period. Importantly, Texas set a "price-to-beat" (which acts as a price floor and is referred to as a price floor hereafter) that the incumbent had to keep through 2006 (approximately $0.08/ kilowatt hour (kWh) in 2002 and $0.15/kWh in 2006) (PUC, 2014 and Payless, 2014). Thus, at the same time Senate Bill 7 deregulated the retail portion in the 5 regions, it placed a temporary price floor on the incumbents in those regions. The initial price floor in 2002 was set 6% less than the regulated rates in January 1999 to provide immediate customer savings (TCAP, 2012). After the initial time period, price floors on incumbent firms were set high enough to attract new firms into the market by providing them a price they could undercut and thereby draw customers away from the incumbent (PUC, 2014 and

TCAP, 2012). The price floor could be adjusted by the incumbent twice a year to better align prices with the wholesale cost of natural gas, subject to the state regulator's approval (PUC, 2014). The fact that the price could be adjusted based on the wholesale cost of natural gas plays an important role in justifying the econometric specification I propose in section 7.

3. Relevant Literature

Many energy and policy papers have tried to determine deregulation's effect on prices. However, most focus only on whether or not residential consumers paid lower prices following deregulation instead of determining the causal effect of deregulation on prices.[14] Other papers compare the prices observed in states that have deregulated to those in still regulated states.[15] Comparing between states not only complicates the study because states may have other factors unaccounted for in such an analysis but it also creates problems when papers use states like Texas as a deregulated state, when in fact much of the electricity market in Texas is not deregulated. Many papers also focus on deregulation's effect on industrial or commercial prices rather than residential prices.[16] Further, the findings are disparate as many find residential consumers pay higher prices while others find residential consumers pay lower prices. Every paper reviewed shows correlation, not causation.

---

[14] e.g. Swadley and Yucel (2011), Kang and Zarnikau (2009), TCAP (2012)
[15] e.g. Swadley and Yucel (2011) and Zummo (2015)
[16] e.g. Rose (2004), Joskow (2006), and Apt (2005)

In line with the above explanation, there is no consensus among earlier studies on how deregulation affects prices. Swadley and Yucel (2011) and Su (2015) find competition led to lower prices for some states (including Texas) but not for others. Zummo (2015) shows that retail electricity prices in deregulated states increased significantly more than they did in regulated states. Basheda et al. (2007) find no difference in the increasing retail rates between deregulated and non-deregulated states following deregulation. Rose (2004) and Joskow (2006) find prices decreased for commercial and industrial consumers, opposite to what Woo and Zarnikau (2009) find. Zarnikau, Fox, and Smolen (2007) also find commercial prices increased. Apt (2005) finds prices did not change for industrial consumers. Joskow (2006) credits legislation and regulated default service for the decrease in residential and industrial prices, not competition. Fagan (2006) shows the difference between actual and predicted electricity prices for industrial customers in deregulated states is much smaller than for customers in non-deregulated states. He determines the smaller change is due to high pre-restructuring prices, not whether or not a state restructured. Whitworth and Zarnikau (2006) show prices in Texas rose faster in deregulated areas while Swadley and Yucel (2011) find the opposite. Axelrod et al. (2006) and Swadley and Yucel (2011) find prices increase when price caps are removed in the deregulated areas while Kang and Zarnikau (2009) find the opposite. Woo and Zarnikau (2009) conclude prices increased in deregulated areas by inspecting graphs and visually comparing the residential price trends of the average of the larger competitive firms, regulated utilities, and two largest municipalities. The three papers most similar to mine are explained in the next three paragraphs.

My research is most closely related to a paper dealing with prices in Texas' electricity market by Whitworth and Zarnikau (2006). They compare prices in a small subset of the regions in Texas following deregulation and look at what happened to prices over time. They analyze graphs that plot the price trends of the different regions to visually determine prices in deregulated areas increased more following deregulation than prices in non-deregulated areas. In order to see if the cost of natural gas has a different effect in deregulated regions compared to non-deregulated ones, they regress, for each company individually, the electricity price to residential consumers on a dummy for whether the company they used was in a restructured market, the cost of natural gas interacted with this dummy, and the cost of natural gas interacted with one minus this dummy (to obtain coefficient estimates on the interaction terms for both deregulated and non-deregulated firms). They compare the regression coefficients from each company and determine that the price decreased immediately following deregulation and that the cost of natural gas effects deregulated regions much more than non-deregulated ones. Relative to my study, Whitworth and Zarnikau do not formalize deregulation's price effect in a regression using a set of controls, are unable to determine the price effect to the customer resulting from the cost of natural gas, and they cannot separate out the effect of deregulation from that of the price floor since their data ends before the floor's removal.

Swadley and Yucel (2011) also try to analyze prices in deregulated regions and the differing effect of input costs. Using state level data, they study the effect of participation rates, price controls, market size, and different methods of electricity generation on retail prices in the states that have deregulated their electricity markets. Using monthly data, they examine the differences in effects using a first difference model. They find that following deregulation some states have lower prices and others do not. They determine natural gas costs have a larger and more statistically significant impact on retail prices than coal costs in deregulated markets and that prices are not affected by temperature. Unlike my paper, they fail to use a control in their analysis and thus assume the prices experienced in the state would have trended in the same manner absent the restructuring in order to make conclusive remarks. Also differing from their paper, I use both deregulated and regulated regions within one state to analyze the differing effect on prices and from the cost of natural gas, avoiding complications that arise when trying to compare electricity markets between states.

Besides contributing to the literature on deregulation's effect on prices and on the differing impact from input costs (i.e. the cost of natural gas), my paper also contributes to the effect after removing the temporary price floor that was introduced to stimulate entry and customer switching. Kang and Zarnikau (2009) find prices in a competitive market decrease in Texas following the price floor removal. Using monthly data from January 2002 to December 2007, they compare prices in deregulated regions from the time of deregulation to one year following the removal of the price floor after controlling for the cost of natural gas and the share of the market not served by the incumbent firm. They conclude a price floor is not necessary once a competitive and mature electricity market exists. Unlike their paper, I use deregulated and non-deregulated regions to establish a valid control and give credible estimates of the effect from the price floor. Further, I am able to study the effect of the removal of the price floor much further out than the year in which it was removed.

My paper improves on past ones in many ways. Importantly, I establish a credible control. Using within state variation of exposure to the deregulation, I estimate the effect on prices from deregulation using a difference-in-difference regression, which has not been done in past papers and allows a causal interpretation under more plausible assumptions. Additionally, I determine the differential impact that the wholesale cost of natural gas has in deregulated and control group markets. I find that the wholesale cost of natural gas must be below $3.15/MBTU for deregulation to decrease residential prices relative to the control regions. Further, I use a different data set than prior papers. The data set spans a much broader time period, from 1994-2012, and encompasses all firms in Texas. Having 8 years of data before the treatment helps to establish that the parallel trends assumption is satisfied, which gives credibility to the control group in the pre period. Having 11 years of data after the treatment allows me to estimate short and long term effects of deregulation and determine the effects of the price floor imposed on the incumbents. By only looking at markets in the state of Texas, I can be sure my results are not biased by state effects. Further, by incorporating the wholesale cost of natural gas, actual number of customers, region fixed effects, dummy variables to capture post 2001 and post 2006, or year fixed effects, I am able to control for and analyze details that other papers did not.

4. Data

The main data source I use comes from the Energy Information Administration (EIA) and is augmented and verified using data from the state regulator and Texas' electricity independent system operator. Within the EIA's database, one can obtain information monthly or annually. While monthly data has its advantages, for the purpose of this paper the annual data is more useful. The annual, panel level data gives each electric company's name, total sales revenue in dollars, total sales quantity in kilowatt hours (kWhs), number of customers served, class of ownership, and average revenue per kWh from 1994 to 2012.[17] The dependent variable used throughout this paper, the average revenue per kWh, is the total sales revenue divided by the total sales quantity (kWh usage).

The EIA also provides data on the average electric power sector price (price it costs the generation companies to buy the fuels) each year for coal, natural gas, nuclear, and others. I also gather the energy production broken down by year and by sector for coal, natural gas, nuclear, wind, and others. All production is given in megawatt hours so it is straightforward to calculate the percent generation mix for each year for each of these sectors. I obtain data on these values from 1994 to 2012, which gives me 8 years of

[17] Many papers use the percent of eligible residential customers taking up competition. My data is richer since I have actual customer counts for each company.

observations before and 11 years after deregulation and results in a total of 3,196 observations, 1,246 of them before deregulation. Some of the cooperatives combine or join with other cooperatives and some regulated investor owned utilities come in and out of the data throughout the studied time period.[18] This change results in an unbalanced panel containing a total of 163 regions throughout 1994 and 2012.[19]

The dependent variable is average revenue per kWh for residential customers, hereafter referred to as average price. I scale it in all graphs and regressions to $/1,000 kWh, what a typical household uses in a month.[20] Municipalities, cooperatives, and regulated independently owned investor utilities only have one plan for their customers, and it is often a step function increasing as usage increases. Through 2006, most firms in the deregulated regions also only offered one plan (Green Mountain Energy, Reliant, and Amigo the main exceptions), but their plans were often a step function decreasing as usage increased. The three already mentioned and many other firms in the deregulated regions started offering multiple plans, from which customers could choose, after 2006. Some companies even offered bonuses when customers signed up. While these different pricing schemes are clearly not the same as average price, the average price is the average of what the entire customer population in the company paid. Therefore, this average price represents the average price consumers paid per kWh—which allows me to avoid

[18] The cooperatives and investor owned utilities appear to change in a random manner. Their combining to or joining of another larger cooperative does not appear to be related to deregulation as it happens throughout the entire timeframe instead of just around the years deregulation occurred.
[19] Appendix Section A.4.3 and Tables A.4 and A.5 present results using a balanced panel data set. Results are almost identical to using the unbalanced panel data set.
[20] The EIA reports that, in 2012, the average residential consumption was 903 kWh per month.

problems that might arise since companies go about charging their customers and earning revenue in different ways. In line with earlier work mentioned in previous sections, I accept the limitation of using average price when companies in fact offered various pricing schemes.[21]

Table 1.1 presents some summary statistics for the years 1999 and 2008. Each year has two subsets: regions that are deregulated/treated and ones that are not (the controls). The average price charged by firms in the deregulated regions and the cost of natural gas increases greatly from 1999 to 2008. The average price charged by firms in the control regions also increases, but by a smaller magnitude than the average price of the firms in the deregulated regions. The number of customers and the quantity of electricity sold both increase at a similar rate between the deregulated and control firms.

In the main analysis of my paper, I present weighted regressions. To come up with the weighting, I separate the companies into two groups, deregulated and controls. To calculate the weight each company gets, I divide the company's total customers by the total customers of the group they fall into each year (deregulated or controls). Therefore, my weight is at the annual-group level. I weight my regressions in order to determine the average price the consumer paid, as opposed to the average price the producer charged. Weighting allows me to capture the fact that the company with more customers has a

[21] I do not control for temperature since previous papers have found it is not a significant determinant of electricity prices (Swadley and Yucel, 2011). I also do not use lags of temperature since my data is annual and most of the lags take two to six months to have any effect (Swadley and Yucel, 2011 or EIA, 2015).

greater impact on the price paid in their group than the company with fewer customers. I present results using non-weighted regressions in the appendix.[22]

5. Main Empirical Strategy and Main Results

5.1. Main Empirical Strategy

I take advantage of the variation in deregulation within Texas to establish a valid control group and estimate a difference-in-difference regression that provides a stronger causal interpretation than prior papers. In order to answer the primary question of this paper--Does deregulation of the electricity market decrease electricity prices to residential consumers?--I ran difference-in-difference regressions that take the following form:

$$p_{jtr} = \alpha_0 + \alpha_r + \alpha_t + \beta * D_{jr} * \boldsymbol{I}_{t \geq 2002} + \delta * D_{jr} * \boldsymbol{I}_{t \geq 2007} + \varepsilon_{jtr}. \quad (1)$$

p_{jtr} is the price charged by firm *j* in year *t* in region r; α_r are region fixed effects; α_t are year fixed effects.[23] $\boldsymbol{I}_{t \geq 2002}$ equals 1 if the year is ≥ 2002 and 0 otherwise. $\boldsymbol{I}_{t \geq 2007}$ equals 1 if the year is ≥ 2007 and 0 otherwise (to capture the effect from the removal of the price floor). D_{jr} is a dummy variable equal to 1 if the firm is in a deregulated region and 0 otherwise. ε_{jtr} accounts for the effect of all unobserved variables which vary over the company level, region level, and time. The coefficients of interest are β and δ which identify, respectively, the impact on price of deregulation and removal of the price

[22] As a reminder, I eliminate Nueces from the data when running my primary regressions presented in the next section. Regression results with Nueces are available upon request. Results are very similar.

[23] Figure 1.3 suggests that the treatment effect from deregulation may vary by year in a relatively nonparametric way. Appendix Section 5 uses deregulation-by-year interactions as opposed to a post 2002 and post 2007 interaction to analyze this possibility.

floor. A causal interpretation resulting from the difference-in-difference regression rests on the fact that prices for the deregulated regions would have continued in the same manner as the control regions absent deregulation.

The variation occurs at the region level; therefore, I follow standard methodology and cluster all standard errors at the region level. As mentioned in the *Background* section, prior to 2002, each firm represents a region. Following 2002, the municipalities, cooperatives, and regulated investor owned utilities still represent a region but the deregulated firm no longer represents a region as it can now enter into four additional regions (reference Figure 1.1). Since my data is at the firm level, I cannot differentiate the price a competitive firm charges in the Dallas region versus what they charge in the Houston region. Therefore, I cannot differentiate between the five deregulated regions following 2002. By combining all five regions into one region, the deregulated region, I can differentiate between the regions represented by all the controls and the deregulated one. This method results in almost 165 regions, with one of them being the treated one. The treated region is the deregulated region which entails the five regions deregulated and is, therefore, treated as only one region before and after the 2002 deregulation in the regression analysis.

One drawback to this is that I cannot tell how the average customer in Dallas or Houston was affected. However, an advantage is that I can tell how the average customer in the deregulated region was affected—which is the answer to the primary question of this paper. Another drawback, and one of more concern from an econometric perspective, is that I only have one treated region. While there were actually five treated regions, I cannot distinguish them in my data and, therefore, group all five regions into one single cluster when calculating standard errors. This is in spite of the fact that the level of variation is finer than the cluster I can create in my dataset. For this reason, I report p-values based on the methods outlined in Conley and Taber (2011) in my main empirical results in brackets.[24] Also, I follow conventional methodology in my analysis using confidence intervals and p-values based on using conventional standard robust clustered errors. Therefore, the reported standard errors in parentheses and asterisks next to the coefficients in the main tables are based on standard robust clustered errors.

To demonstrate robustness of these results, I run regressions after limiting my treated group to the five incumbents and comparing them to different subsets of the controls. When focusing in on the incumbents, I use company instead of region fixed effects and calculate clustered standard errors at the company level in addition to the methods suggested in Donald and Lang (2007) and Bertrand, Duflo, and Mullainathan (2004). Results and details are given in the robustness section.

5.2. Main Empirical Results

One important condition for the credibility of a difference-in-difference estimation strategy is that the treated and control groups should have parallel trends prior to the treatment. Figure 1.3 shows the weighted average prices to residential customers

[24] Conley and Taber's method uses the residuals of the estimating equation run without the variable of interest included in the regression in order to obtain the empirical distribution. The p-value is obtained by comparing the actual estimate to this empirical distribution.

in the deregulated and control regions in Texas from 1994 to 2012.[25] The scale on the vertical axis is the average price paid in $/1,000 kWh. Year is on the horizontal axis. The blue, X-marked line represents the average price paid by consumers in the deregulated regions. The red, diamond-marked line represents the average price paid by consumers in the control regions. The red vertical line at 2001.5 denotes just prior to the 2002 deregulation. The red vertical line at 2006.5 denotes just prior to the removal of the price floor.

Inspecting Figure 1.3 reveals important points. Importantly, the trends before 2002 are parallel, establishing validity of the control group. Following 2002, there is a clear separation in prices between the deregulated and control regions. The decrease in average price for the deregulated regions from 2001 to 2002 immediately following deregulation is expected since, as described in the *Background* section, the price on the incumbent was set 6% less than the regulated rates in January 1999 to provide immediate customer savings. After 2002, the prices in the deregulated regions increase at a much greater rate than the prices of the controls, suggesting deregulation causes an increase in prices. In the deregulated regions there is a slight decrease in prices after 2006, when the price floor was removed, and there is a sharp decrease in prices after 2009. Prices in the control regions trend up from 2002 to 2006, which makes sense since the cost of natural gas increased so much during this timeframe (this effect will be explored in the second half of the paper). Prices in the controls regions remain relatively stable from 2006 on.

---

[25] The weighting is performed from here on using the method described in the *Data* section. Results of regressions without weighting are presented in the Appendix.

Table 1.2 provides the empirical results for equation (1). Each of the regressions in this table are run at the individual level and are weighted. The left hand column of the table lists the independent variables of interest and each subsequent column represents a different regression corresponding to equation (1). The coefficients in this table answer the primary question of this paper: how did deregulation affect the prices to residential consumers? Column (1) depicts equation (1) without time or region fixed effects, but instead indicators for the deregulated region, post 2001, and post 2006. Column (2) uses year fixed effects instead of the post 2001 and post 2006 indicators. In addition to year fixed effects, column (3) uses region fixed effects instead of the deregulated indicator. Column (4) adds in a control—quantity. Regardless of the specification used, results are robust across specifications. Column (3) is my preferred specification. Empirical justification and discussion of quantity in the electricity market being exogenous is provided in the appendix.

Column (3) shows that the average customer in the deregulated region paid over $14 per month more than regulated customers due to deregulation from 2002 to 2006. From 2007 on, this value increases to almost $24 ($14.46+$9.30). Clustering standard errors in the standard fashion, at the level of variation which is at the region level here, gives significance at better than the 1% level.[26] Further, $\beta + \delta$ is significant at better than the 1% level.[27] Compared to the mean of the dependent variable, the average

[26] The values are significant at better than the 5% level using the Conley-Taber method for β but lose significance for δ. However, $\beta + \delta$ is significant at the 5% level using the Conley-Taber method.
[27] The standard error of $\beta + \delta = 1.686$ when clustering standard errors at the region level, resulting in a p-value = 0.000. The Conley-Taber p-value = 0.031

customer in the deregulated regions paid almost 15% higher from 2002 to 2006 and 25% more from 2007 on, compared to the average customer in the control regions; due to deregulation and the price floor.[28]

6. Model

Proponents of deregulation argue we would see results opposite of those presented in the prior section. They argue deregulation would bring about lower prices, not higher ones. In this section, I present two plausible reasons why this did not happen. One reason is that electricity prices to residential consumers in regulated regions are based on average cost (AC) pricing while prices in deregulated regions are based on marginal cost (MC) pricing. The other is that firms in deregulated regions are more exposed to current natural gas prices, due to the way they purchase electricity for their customers, than the firms in the regulated/control regions.

6.1. Pricing Based on Marginal versus Average Costs

Regulated firms have their prices set by a state regulator who applies a common rate of return pricing formula regulated firms can charge their customers (PUC, 2015). The state regulator's basic rule making formula is as follows: multiply the firm's costs of utilities and useful assets or rate base by a reasonable rate of return (often close to 10%); add in the fuel costs, purchased power costs, and the operations and maintenance costs; and then divide this summation by the number of customers or quantity of electricity sold (Zarnikau, 2015). Thus, the formula takes average costs and gives the company a

---

[28] Appendix Section A4.c and Tables 4a and 5a present results using a balanced panel data set. Results are almost identical to using the unbalanced panel data set.

nominal profit. These average costs include many different costs but are mainly affected by the costs of the fuels used to produce electricity and the purchased power, both of which are not marked up.

The retail portion of the deregulated electricity market is accurately represented by Bertrand competition, where firms compete on price (Borenstein and Holland, 2005). In Borenstein and Holland's electricity market model, the retailers are price takers because they are selling a homogeneous product and face no real capacity constraints. Thus, once they are open to retail competition, prices in the retail market trend towards marginal costs as long as two firms exist in the market.[29] The standard economic argument justifies why only two firms are necessary in the electricity market for it to become a perfectly competitive one. [30] If a firm offers a higher price than its competitor, they will find themselves without customers. A firm will capture the entire market if it offers a lower price than its competitor. Due to these two pricing situations, prices will trend to MC. If a firm offers a price lower than where MC = AC, the firm will not cover costs and will eventually go out of business. Even if competition is not perfect, prices will still be related to MC, not AC.[31] Below, I empirically test whether retail prices track MC.

As explained above, in deregulated regions prices are tightly linked to marginal costs, whereas, in regulated regions prices are based on average costs. The driver of the

[29] Borenstein and Holland (2005) provide a more detailed overview for the interested reader.
[30] Puller (2007) uses empirical evidence to refute that a small number of firms in the electricity market yield market power and withhold quantity to increase prices.
[31] For example, see Mahoney and Weyl (2014).

average costs is average fuel costs. Average fuel costs represent a mix of fuel choices and, with the exception of natural gas, have been relatively stable in the past 20 years (EIA, 2015). Therefore, the retail price in the regulated regions is a function including the average costs of electricity which is primarily made up of natural gas, coal, and nuclear fuel. In contrast, the retail price in deregulated regions is a function of the MC of electricity.[32] In Texas, the cost of natural gas almost always determines the marginal cost of electricity and is thus considered the marginal fuel.[33] Equations (2) and (3) show this in functional form. Equation (2) shows that the price charged by firm *j* in deregulated region *d* is based on the marginal cost of electricity and the demand for electricity in the deregulated region. The marginal cost of electricity is based on the cost of natural gas. Equation (3) and (3b) show that the price charged by firm *j* in regulated region *r* is based on the average total costs to the firm, which are based on the average costs of electricity and other inputs.

$$p_j^d = f\left(MC_{e,}D^d\right) \, where \, MC_e = \; f_1\left(p_{ng}\right) \qquad (2)$$

$$p_j^r = h(AC_T) \; (3)$$

$$AC_T = h_1\left(AC_e, AC_{other\_inputs}\right) and \; AC_e = \; h_2\left(p_{coal}, p_{nuclear}, p_{ng,} p_{others}\right) \qquad (3b)$$

$h_2\left(p_{coal}, p_{nuclear}, p_{natural\ gas,} p_{others}\right)$ represents a weighted average of the cost of all possible fuel inputs. Assume *f*(.)', *f*$_1$(.)' *h(.)*', *h*$_1$*(.)*' and *h*$_2$(.)' > 0.

[32] See Woo and Zarnikau, 2009; Whitworth and Zarnikau, 2006; or Swadley and Yucel, 2011.
[33] See references in footnote above and Appendix Section A3 for a detailed explanation of this sentence. The basic reason is that coal and nuclear are often used at maximum capacity while natural gas supplements demand and, in the studied time interval, was more expensive than coal and nuclear.

Figure 1.4 illustrates why prices may not decrease when we deregulate the electricity market and shift to marginal cost pricing, and what we expect to see after the price floor is removed.[34] If the market faces demand D_L it will move from point A to B when it is deregulated, increasing quantity from S_L to Q_L, and decreasing price from R_L to $P_{L.}$ However, if the market faces demand D_H then when it becomes deregulated it will move from point D to point C, decreasing quantity from S_H to Q_H, and increasing price from R_H to $P_{H.}$ While lower prices are touted as the primary reason to allow deregulation, the theory shows that deregulation may in fact increase prices.

In either demand situation, the price floor is binding. Since the incumbent cannot price below the price floor, incoming firms can enter the market and price below the incumbent to attract customers but still make profits. We expect to see prices decrease when the price floor is removed as the incumbent could then compete against firms on price. This, of course, assumes the market experiences some type of consumer inertia problem.[35] If there was no inertia problem, then all customers would leave the incumbent since other firms offer essentially the same product for a lower price. The residential price effects seen in Texas following deregulation and removal of the price floor suggest demand $D_{H,}$ a binding price floor (as depicted in the figure), and consumer inertia all described Texas' electricity market from 2002 through the removal of the price floor.

---

[34] The model builds upon Woo and Zarnikau (2009).
[35] The consumer inertia problem is discussed at length in Giulietti et al. 2005 and Horatcsu et al., 2012.

6.2. Bilateral Contracts, Day-Ahead Market, Real-Time Market

The second reason prices may have increased more in the deregulated regions follows from how firms in Texas purchase electricity for their customers. In Texas, there are three ways to buy electricity: bilateral contracts, the day-ahead market, and the real-time market. The percentages and amounts purchased in these three markets are closely protected by businesses, and are not publicly available.[36] 80%-95% of electricity in Texas is purchased through bilateral contracts, with municipalities and cooperatives making up the majority of the purchases (ERCOT, 2015 and PUC, 2015). Bilateral contracts agree upon prices for a specific duration. When purchasing electricity in the day-ahead and real-time markets in Texas, a company pays the cost of the most expensive generator that must be used to satisfy demand. This cost is determined by the marginal cost of producing the last unit of electricity quantity. In these two markets, Texas' electricity operator determines how much electricity will be needed to satisfy demand and accepts the bids, from lowest to highest, of all the generators needed. All generators are paid the highest price bid of the generator that must be turned on. Anyone buying electricity in this market, i.e. the retailer, pays this price. From 2002 to 2012, the cost of natural gas almost always determined the price of the most expensive generator (ERCOT, 2015).

Due to the consistency of their customer base, knowledge of how and when their customers use electricity, and relative ease of predicting future electricity consumption,

[36] The information in the rest of this section is through many interviews (some confidential) with employees at the state regulator; employees at Texas' independent system operator, employees of different deregulated companies, municipalities, cooperatives, and faculty members at the University of Texas.

the regulated investor owned utilities, municipalities and cooperatives enter into 10, 15, and 30-year bilateral contracts that cover the majority of the electricity demanded by their customers (PUC, 2015; ERCOT, 2015; Webber, 2015). Due to the ambiguity of their customer base, uncertainty of the customer's demand for electricity, and difficulty with predicting future electricity consumption, the majority of the firms in the deregulated regions enter into 1-3 year bilateral contracts that cover a small portion of their customers' demand. These firms rely on the day-ahead and real-time market to purchase the majority of electricity for their customers. Having a large percentage of the electricity they need negotiated and paid for in bilateral contracts as well as having contracts that span such long durations, regulated utilities, municipalities, and cooperatives are greatly hedged against rising fuel costs. Having more electricity bought in the day-ahead and real-time markets, firms in the deregulated regions are more exposed to current day prices, which, as explained earlier, are normally based on the cost of natural gas.

As explained above, short duration contracts and more exposure to the day-ahead and real-time markets are typical for firms in the deregulated regions. Long duration contracts and less exposure to the day-ahead and real-time markets are typical for the control firms/regions. Further, the firms in the deregulated regions use marginal cost pricing while the firms in the regulated regions use average cost pricing. These differences all lead to the same two predictions. First, the retail price in deregulated regions should be more sensitive to the cost of natural gas than the control regions.

Second, the retail price in the control regions should move in the same direction but with less magnitude than the retail price in the deregulated regions. I cannot distinguish the effect on prices from contract length, market exposure, and type of pricing used due to the correlation between them and the type of region in which they occur (deregulated or control). Therefore, the coefficients in my regression equation to follow capture the combined effects of all these factors.[37]

7. Empirical Strategy and Results Evaluating the Role of Natural Gas

7.1. Empirical Strategy

Due to the differences explained in detail above, the price charged to residential consumers in the deregulated markets is more closely tied to the cost of natural gas than is the price charged to residential consumers in the control markets. Figure 1.5 depicts the cost of the three main fuels used in Texas to produce electricity: natural gas, coal, and nuclear. It also depicts the weighted average cost of all three.[38] As explained, these costs are the key variable explaining the final price generators charge for electricity produced (Webber, 2015). Due to the high costs of natural gas during the studied timeframe, the figure helps depict why natural gas most often determines the most expensive generator that must be turned on and thus the marginal cost of electricity. The horizontal axis depicts the year and the vertical axis depicts the average cost of the fuel in $/MBTU. As

[37] Less important and more subtle reasons that the cost of natural gas affects the deregulated regions differently than the control regions are provided in the appendix.

[38] The weighted average price takes into account the percent used to produce electricity and the price of the fuel.

there is a national market for these fuels, the price in Texas is representative of the price in other states (Zarnikau, 2015).

Figure 1.5 illustrates that the price of natural gas experienced an upward trend after deregulation occurred and a downward trend following removal of the price floor. It also shows the price of nuclear and coal remained very stable throughout the studied time interval. It demonstrates that companies that also use coal and/or nuclear will have more stable and lower prices on average than companies that primarily or only use natural gas. It also illustrates that the price of natural gas is highly correlated with the weighted average price of the three fuels. The figure helps depict why price changes will be greater in magnitude for the deregulated regions whose prices are based on marginal costs than the control regions that price based on average costs.

Figures 1.3 and 1.5 are consistent with the model described in the *Models* section. Comparing the price of natural gas and the weighted average price of the three fuels, illustrated in Figure 1.5, with the weighted average price charged by firms in the deregulated regions and the weighted average price charged by firms in the control regions, illustrated in Figure 1.3, one can see the correlations. Electricity prices in the deregulated regions follow a similar trajectory to the price of natural gas, which determines the marginal cost of electricity. Electricity prices in the control regions follow a similar trajectory to the weighted average price of the three fuels, which make up a large part of the firms' average costs.

In Texas, natural gas is the main fuel used to generate electricity. Figure 1.6 illustrates that approximately 50% of the electricity in Texas is generated using natural gas, 38% is generated using coal, 10% is generated using nuclear, and the remaining amount comes from wind and other sources. The horizontal axis of Figure 1.6 depicts the year. The vertical axis depicts the percent of the fuel used to generate electricity. Since 2007, wind has gained a greater share and is responsible for just shy of 10% of the electricity generated by 2012. This figure supports why the cost of natural gas has such a heavy influence on the weighted cost of the fuels used to produce electricity.

Decoupling the effects from the cost of natural gas becomes more important after deregulation because, as explained above, natural gas prices affect the deregulated regions much differently than the control regions. It is important from a policy perspective to know the effect of deregulation, without it being confounded by other variables. Due to this possibility, the last set of regressions run are the same as equation (1) with one major difference—they allow more flexibility by interacting the price of natural gas (depicted as PNG in equation (4)) with the key variables. To clarify, this difference-in-difference equation takes the following form:

$$\begin{gathered} p_{jtr} = \alpha_0 + \alpha_r + \alpha_t + \beta_1 * D_{jr} * \boldsymbol{I}_{t\geq 2002} + \delta_1 * D_{jr} * \boldsymbol{I}_{t\geq 2007} + \varepsilon_{jtr} + \\ \omega_1 PNG_t * D_{jr} + \omega_2 PNG_t * \boldsymbol{I}_{t\geq 2002} + \omega_3 PNG_t * \boldsymbol{I}_{t\geq 2007} + \\ \beta_2 PNG_t * D_{jr} * \boldsymbol{I}_{t\geq 2002} + \delta_2 PNG_t * D_{jr} * \boldsymbol{I}_{t\geq 2007} \end{gathered} \tag{4}$$

Equation (4) is the same as equation (1) plus it interacts the price of natural gas with everything except α_r and α_t (but it does interact with the two appropriate time and deregulated region indicators). This equation allows one to see how the price of natural gas affects prices to residential consumers following deregulation and allows it to have different effects in the deregulated and control regions. It helps answer the follow-up question in this paper: what is the differential impact resulting from input costs on the price that residential consumers face in the deregulated regions versus the other regions?

The coefficients of interest from equation (4) are $\beta_1$and β_2 from 2002 to 2006. They include $\beta_1, \beta_2, \delta_1 and\ \delta_2$ from 2007 on. In isolation, β_2 ($\beta_2 + \delta_2$) estimates the change in prices from 2002-2006 (2007-2012) to the average consumer in the deregulated regions relative to the average consumer in the control regions given the price of natural gas increases by $1/MBTU. For 2002 to 2006, solving $\beta_1 + \beta_2 * PNG_t < 0$ for the PNG_t provides an estimate for what the price of natural gas must be for deregulation to lead to decreasing prices to consumers in deregulated regions relative to control regions. This happens whenever:

$$PNG_t < -\frac{\beta_1}{\beta_2} \quad (5).$$

For 2007 on, using the same methodology, deregulation leads to decreasing prices to consumers in deregulated regions relative to control regions whenever:

$$PNG_t < -\frac{(\beta_1 + \delta_1)}{(\beta_2 + \delta_2)} \quad (6)$$

7.2. Empirical Results Evaluating the Role of Natural Gas

Figure 1.7 depicts the difference in the weighted average prices between the deregulated and control regions and the price of natural gas. The blue, solid-diamond marked line is the weighted difference between the firms in the deregulated regions and the controls. The red, open-diamond line is the price of natural gas. The average price difference, in \$/1,000 kWh (this is the average paid per month), is on the left hand vertical scale and the price of natural gas, in \$/MBTU, is on the right hand vertical scale. Year is on the horizontal axis. This graph is shown so the reader can visually see the difference between the deregulated and control firms' prices and the price of natural gas on one graph. It depicts a pictorial representation of the difference-in-difference regression and shows the trends were very similar prior to 2002--as the difference is quite stable from 1994 to 2001, at around \$9, and then greatly increases following 2002. It also shows a correlation between these values and the price of natural gas which, along with the explanation in the *Model* section, demands further inspection.

Table 1.3 provides the empirical results for equation (4). The table and specifications are structured similarly to Table 1.2.

Column (3) shows that, from 2002-2006, for every \$1/MBTU increase in the price of natural gas, the average consumer in the deregulated region paid an extra \$4.84/1,000 kWh due to deregulation. This value decreases to \$2.30/1,000 kWh from 2007-2012 ($\beta_2 + \delta_2$ = \$2.30 is significant at better than the 1% level). Clearly, the price of natural gas impacts the deregulated and control regions differently.

As expressed earlier, equation (4) allows for a calculation to determine what the price of natural gas must be in order for deregulation to cause retail prices to decrease relative to retail prices in control regions. Solving equation (4) for equations (5) and (6) gives this value. Using the results from Table 1.3, column (3) and solving equation (5), one can calculate that, from 2002 to 2006, the price of natural gas would have needed to be less than $3.15/MBTU for deregulation to have caused the price producers charge to decrease, relative to retail prices in control regions. The red, horizontal line in Figure 1.5 depicts the price of $3.15/MBTU. As shown, the price of natural gas was not below this value from 2000 to 2011. This value shows that deregulation could lead to lower retail prices in the short run, relative to retail prices in control regions, if the price of natural gas is low enough.

Using the results from Table 1.3, column (3) and solving equation (6), one can calculate that from 2007 on, the price of natural gas must be negative for deregulation to lead to decreasing retail prices relative to the control regions. A negative price, obviously, cannot happen. This result is likely not applicable since the price of natural gas has decreased below a certain threshold that precludes it from determining the marginal cost of electricity. The price of coal, or another fuel, would eventually take over as the input responsible for the marginal cost of electricity which would determine the final prices to consumers in the deregulated regions.

8. Robustness Checks

In this section, I present figures and regression results that focus on subsets of the controls that are more like the deregulated firms in some specific way. I also present results focusing in on subsets of the deregulated firms and controls to provide robustness to the main results.

Figures 1.8-1.11 present a graphical depiction of the weighted average prices after focusing on a subset of controls and/or deregulated firms. Each graph is of the same format with average price/1,000 kWh on the vertical axis and year on the horizontal axis. The blue, solid-diamond marked line represents the weighted average price of the deregulated firms in Figure 1.8 and the weighted average price of the five incumbents in Figures 1.9-1.11 (a subset of the deregulated firms). The other lines represent a specific set of controls labeled in the legend at the bottom of each figure. All four figures have the same important characteristics. In all of these figures there is a parallel trend prior to 2002; a clear break after 2002 in the parallel trend with the residential prices of the deregulated or incumbent group increasing at a much greater rate than the controls, and a stagnation and eventual decrease after 2007 for the deregulated region or incumbent firms while the control regions' residential prices, in general, stay relatively flat. The parallel trends prior to deregulation lends credibility to these groups being valid controls; the break after 2002 lends validity to deregulation's causal effect on prices; and the break after 2007 lends credibility to the price floor affecting prices.

Table 1.4 presents regression estimates when focusing in on the subsets represented by Figures 1.8-1.11. Each column corresponds to a subset of the population represented in a figure or multiple figures. Column 1 corresponds to Figure 1.8, column 2 corresponds to Figure 1.9, columns 3 and 4 correspond to Figure 1.10, and column 5 corresponds to combinations of Figures 1.9-1.11. The first column of Table 1.4 depicts results running regression equation (1). The final 4 columns follow the same form as equation (1), but since they use the 5 incumbents instead of all firms in the deregulated regions, I use company fixed effects as opposed to regional fixed effects. [39]

Standard errors are calculated slightly different in this table (and in Table 1.5). The standard errors reported are clustered at the region-level for column 1 and company-level for columns 2-5. Asterisks signifying significance next to the coefficients are denoted using these robust standard errors. In column 1, since there are 74 control clusters and only 1 treated cluster, I report Conley-Taber p-values in brackets. Following Donald and Lang (2007) and Bertrand et al. (2005), I report weighted bootstrap (1,000 times with replacement) p-values in brackets for columns 2-5 due to the small number of total clusters but larger number of treated clusters (five as opposed to one).

The five subsets are chosen to show results when focusing in on groups very similar in some measure above and beyond the general results using all firms. Since each of the subsets chosen existed from 1994 to 2012, results presented in this table are taken from a balanced panel. Column 1 uses all firms in the deregulated regions but only the municipalities as controls because, unlike any cooperatives or regulated investor owned utilities, some municipalities base the prices they charge off marginal costs following deregulation (some municipalities based prices off marginal costs prior to 2002 also). Since some municipalities base prices off average costs while others use marginal costs, the results in this column lend support that using the day-ahead and real-time market as opposed to long term bilateral contracts has a large effect on the residential prices to

[39] Using company fixed effects has the added benefit of their being 5 treated groups, instead of just 1.

consumers. However, since many municipalities base prices off average costs, the effect of average versus marginal costs and type of contracts used to purchase electricity still cannot be separated focusing in on this set of controls.

Column 2 uses only the four regulated investor owned utility companies as the controls and narrows down the deregulated firms to only the incumbents. This is done in order to have firms most similar in structure and similar in size before deregulation and consequently similar in size following deregulation. Column 3 uses the 5 incumbents and the 5 biggest municipalities so I can compare firms similar in size and similar in what electricity prices to residential consumers are based on following deregulation, that is, marginal costs. Column 4 uses the 5 incumbents and the 5 biggest controls – which include 2 municipalities, 2 cooperatives, and 1 investor owned utility. These 5 controls are used because, out of all possible control firms, they are the most similar in size to the 5 incumbents. Column 5 increases the prior subset of controls by using the biggest firms most similar in size to the incumbents – which consists of the 5 largest municipalities, 3 largest cooperatives, and the 4 investor owned utilities. This is done to increase the number of the controls while still providing firms similar in size.

As can be seen from Table 1.4's coefficients, regardless of the subset used, coefficients are strikingly similar in magnitude and significance. In every case, when using clustered robust or weighted bootstrap standard errors, $\beta+\delta$ is significant at the 1% level (5% level when using Conley-Taber in column 1). Further, the coefficients are similar in magnitude and significance to the main regression results presented in Table

1.2 column 3, with the only difference being that they are larger (β is about 20% larger, δ is about 50% larger, and $\beta + \delta$ is about 30% larger). The fact that these subsets of controls, arguably more similar to the firms in the deregulated regions than using all possible firms, produce coefficients similar in magnitude and significance to the results in the main empirical analysis provides robustness to the main results in Tables 1.2 and 1.3.[40]

Figure 1.12 and Table 1.5 follow the same process described above but use equation (4) to show robustness for the results presented in Table 1.3. Figure 1.12 depicts the weighted average price of the five incumbents, the four regulated investor owned utilities, and the price of natural gas. The weighted average price is depicted on the left hand side vertical axis and the price of natural gas is depicted on the right hand side vertical axis. Year is on the horizontal axis. The conclusions and analysis are the same as described above. Table 1.5 provides robustness supporting Table 1.3. Results, both in magnitude and significance, in Table 1.5 are very similar to each other. The results are similar to or greater than those in Table 1.3, column 3 (magnitude wise). β_1 and β_2 range from the same to almost 70% larger (in magnitude) and δ_1 and δ_2 range from the same to about twice as large (in magnitude).[41.42]

[40] Non-weighted regressions support these findings and are available upon request.
[41] Standard errors are calculated and depicted the same as detailed for Table 4. Conley-Taber p-values are depicted in [] in column 1 and weighted bootstrap p-values are depicted in [] in columns 2-5.
[42] Non-weighted regressions support these findings and are available upon request.

9. Conclusion

Due to electricity deregulation in Texas and the rising price of the marginal fuel used to produce electricity (the cost of natural gas) without a corresponding increase in the cost of the other fuels, customers in the deregulated regions paid higher prices than customers in the municipalities, cooperatives, and regulated investor owned utilities. Compared to the average customer in the control regions, the average customer in the deregulated regions paid an extra $867 from 2002 to 2006 ($14/month * 12 months * 5 years) and an extra $1,710 from 2007 to 2012 ($23.75/month * 12 months * 6 years) due to deregulation. This obviously runs counter to the main benefit touted by proponents of deregulation—that deregulation will lead to lower prices. Municipalities and cooperatives within Texas, policy makers in Texas and other states, and policy makers in other countries should consider these results when deciding to deregulate or re-regulate their areas. This price differential due to deregulation is especially disheartening for proponents of deregulation, as Texas is touted as the "success" story in North America.

The method used in this paper finds the price of natural gas must be low for deregulation to lead to lower prices.[43] Since the price of natural gas rarely dips below these low levels found in section 7.b, deregulation in an area where the predominant fuel used is natural gas will rarely result in decreased prices to consumers. These results suggest that deregulation will not decrease prices to the average consumer and thus should not be implemented by policy makers who aim to decrease prices to their

[43] It should be noted that the data used in this paper only includes the electricity markets in Texas. Extrapolation of these results to other electricity markets in other states should be taken with caution.

constituency. Unless a policy maker expects the cost of natural gas to drastically fall, deregulation will lead to results suggested in this paper--customers will pay higher prices if the market becomes deregulated (at least in Texas's market, where natural gas is the dominant fuel and the cost of it greatly exceeded the costs of the average fuel costs). My results show that, roughly, a 20% increase in the price of natural gas leads to a 5% increase in the price of electricity to residential customers in deregulated regions compared to regulated regions.

Once taking into account the cost of the marginal input fuel, we see deregulation can help electricity markets decrease prices, but only if the cost of the marginal input fuel stays very low. As explained above, the deregulated market is tied closely to the cost of the marginal input fuel while the regulated one is tied closely to average prices of all the fuels. As prices approach the marginal cost, the economy may become more efficient from an economic perspective if deadweight loss decreases (this was not studied in this paper), but this need not result in lower consumer prices. If the cost of the marginal input fuel decreases below a certain threshold (in Texas, this means the price of natural gas needed to decrease below \$3.15/MBTU) then the deregulated markets may observe lower prices. If the cost of the marginal input fuel stays stagnant, increases, or does not decease below this value, then the deregulated markets may observe higher prices—as they did in Texas.

While other states may and probably do use a different mix of fuels, the relationship between MC and AC remains when moving from regulated to deregulated.

If there is not a drastic change in any fuel prices, but rather a steady or no change, then the market that observes lower prices will depend on the relationship between the marginal and average cost of the fuels at the time. If the marginal cost is greater than the average cost, deregulating the electricity markets will lead to higher prices. If the opposite is true, deregulated markets implemented similarly to how they were in Texas would lead to lower prices.

This paper shows that consumers paid higher prices in deregulated electricity markets in Texas. It also shows that deregulated markets can lead to higher prices. Deregulated electricity market's relationship with MC and the corresponding link within Texas between MC and the cost of natural gas led to higher prices. As described, these same inputs could lead to lower prices, given the right circumstances. Unfortunately, for the residential customers in the deregulated regions in the state of Texas, this is not what happened, and they paid a hefty price for their electricity due to this policy change.

Figure 1.1: Firm and Region Relationship

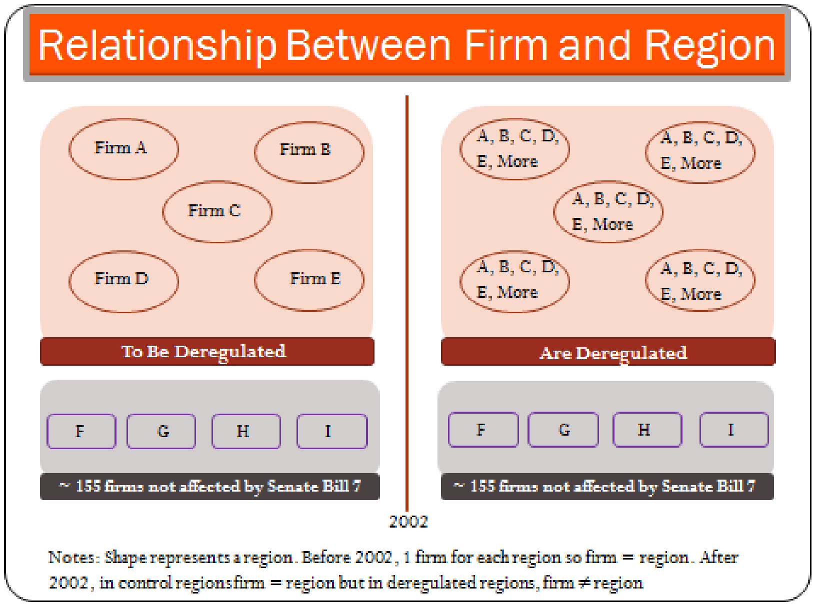
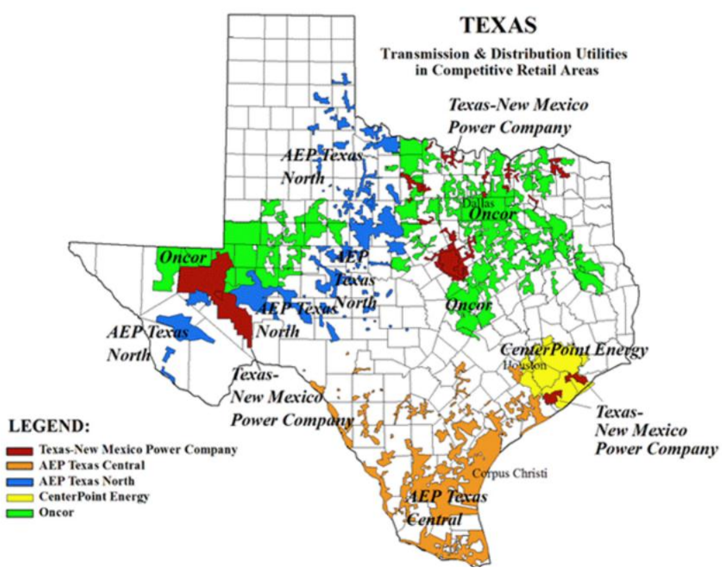
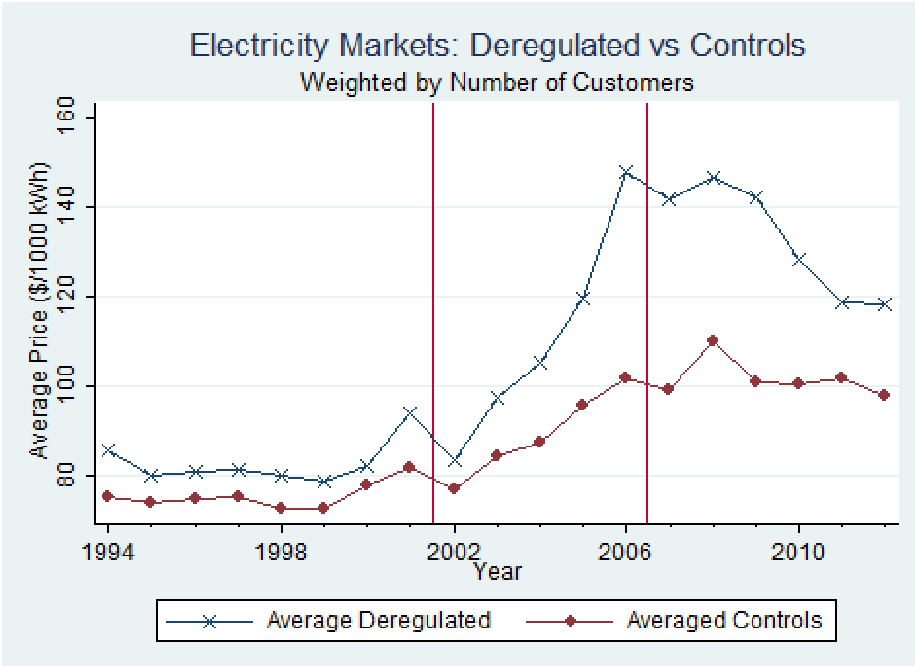


Figure 1.2: Deregulated Regions in Texas



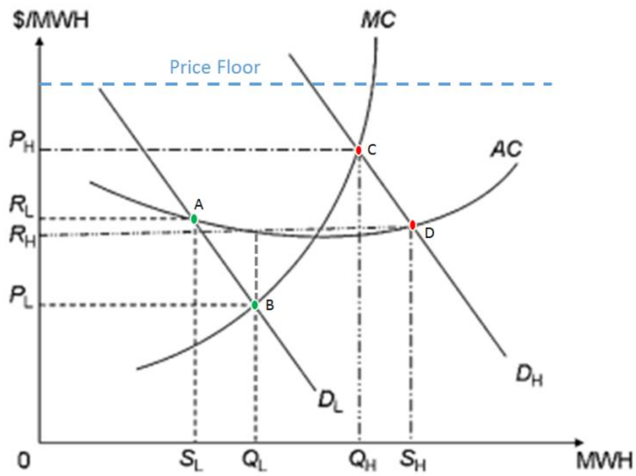
Notes: Shaded regions represent regions deregulated by Senate Bill 7. Each color corresponds to the deregulated region identified in the legend. Source: PUC, 2015.

Figure 1.3: Average Price of Deregulated and Controls Regions



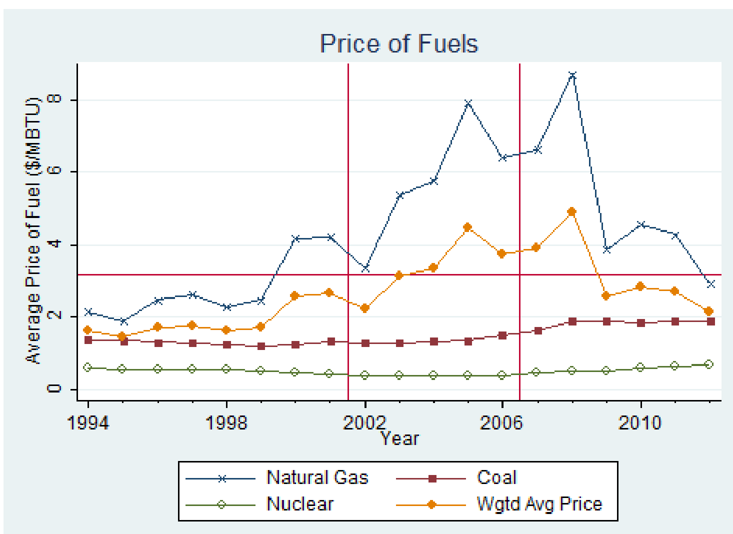
Notes: The figure above shows the weighted average price of the deregulated regions and the control regions each year. Average price, in $/1,000 kWh, is on the y-axis and year is on the x-axis. The prices depicted are weighted by a firm's number of customers. The first vertical red line is just prior to the 2002 deregulation and the second vertical red line is just prior to the removal of the temporary price floor placed on the incumbents.

Figure 1.4: Average Cost vs. Marginal Cost in the Electricity Market



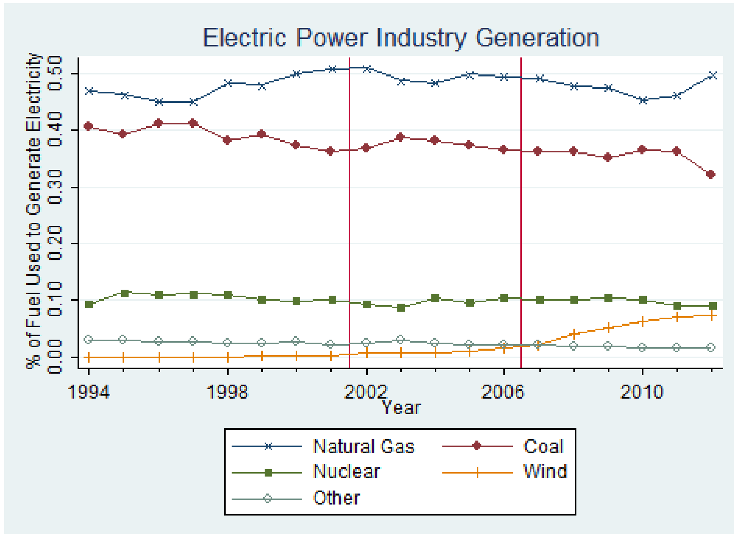
Notes: The figure above depicts the price of electricity ($/MWH) on the y-axis and quantity of electricity (MWH) on the x-axis. Average cost (AC) and marginal cost (MC) curves are drawn to depict the hypothetical electricity market. Demand D_L and demand D_H depict two different possible demand scenarios. The hypothetical price floor, which is based on the price of natural gas, is depicted as a blue-dashed horizontal line.

Figure 1.5: Price of Fuels used to Generate Electricity



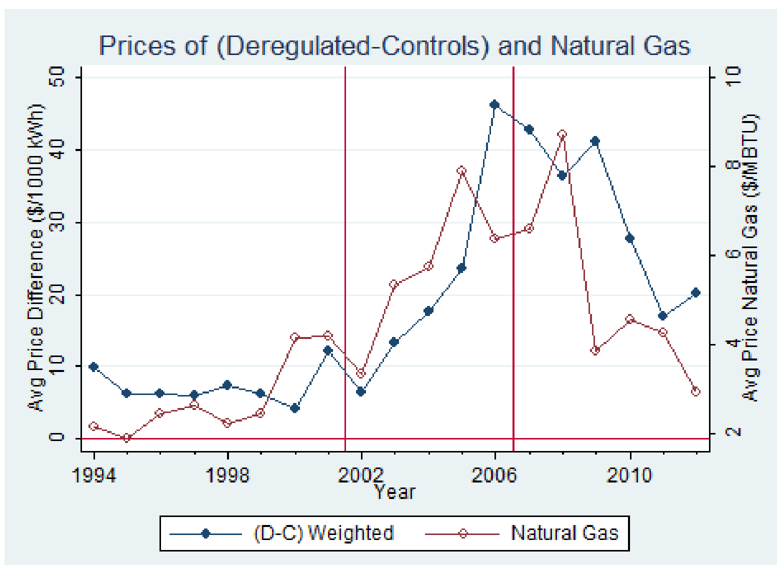
Notes: The figure above depicts the average price of natural gas, coal, nuclear, and the average weighted price of all the fuels used to produce electricity. The average weighted price is calculated using the price of the fuel and proportion of the fuel used for electricity production. See Figure 1.3's notes for more details.

Figure 1.6: Percentage of Fuel Used to Generate Electricity in Texas



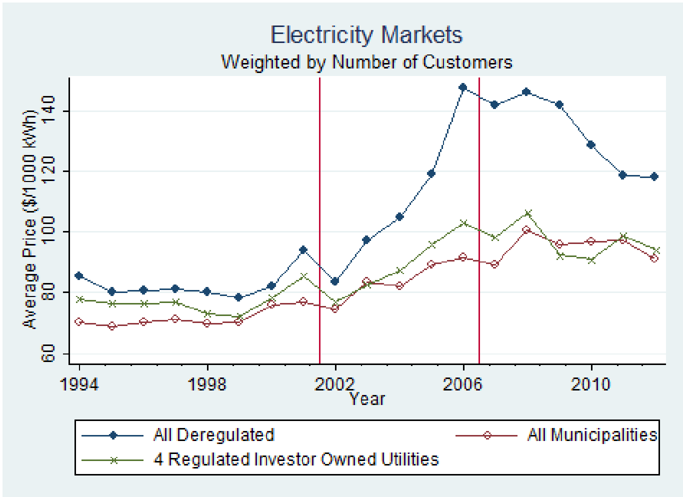
Notes: The figure above shows the proportion used of each fuel used to produce electricity. Percentage of fuel used is on the y-axis and year is on the x-axis. Each line represents a different fuel as labeled in the legend. See Figure 1.3's notes for more details.

Figure 1.7: Price of (Deregulated – Control Firms) and the Price of Natural Gas



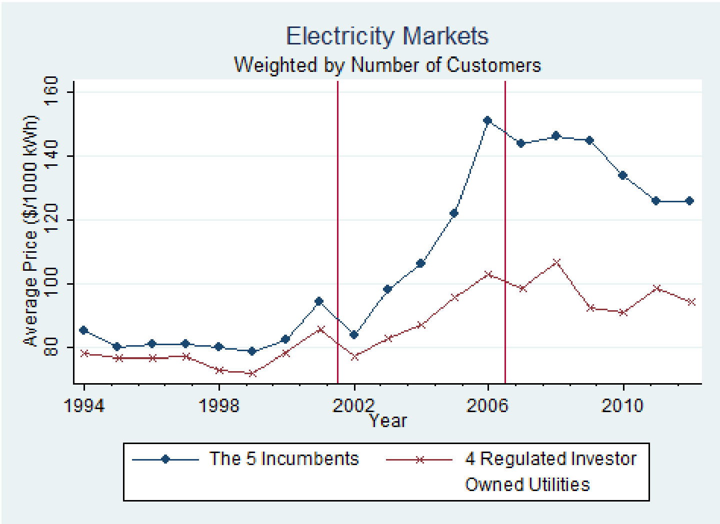
Notes: The figure above depicts the weighted average price difference between the deregulated and control regions and the average price of natural gas. The average price of natural gas, in $/MBTU, is on the right hand vertical axis. See Figure 1.3's notes for more details.

Figure 1.8: Average Price of Deregulated Firms, Municipalities, and Investor Owned Utilities



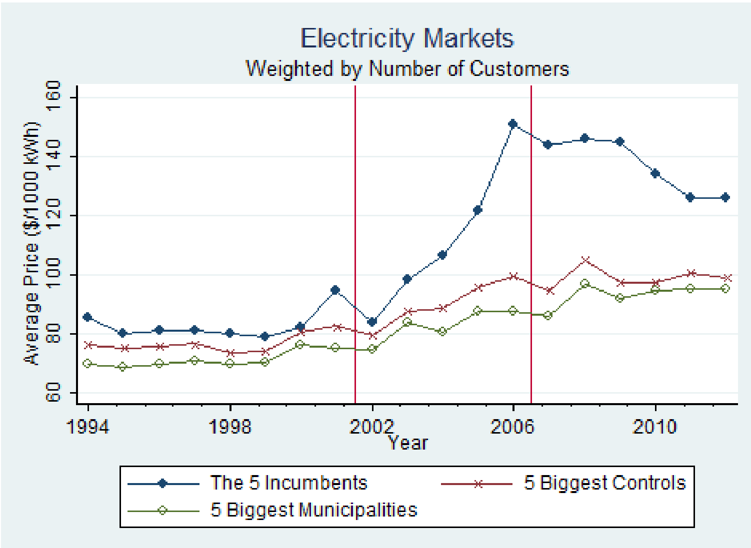
Notes: The figure above depicts, each year, the weighted average price of the deregulated regions, all the municipalities, and the four regulated investor owned utilities not deregulated by Senate Bill 7. See Figure 1.3's notes for more details.

Figure 1.9: Average Price of 5 Incumbents vs. 4 Regulated Investor Owned Utilities



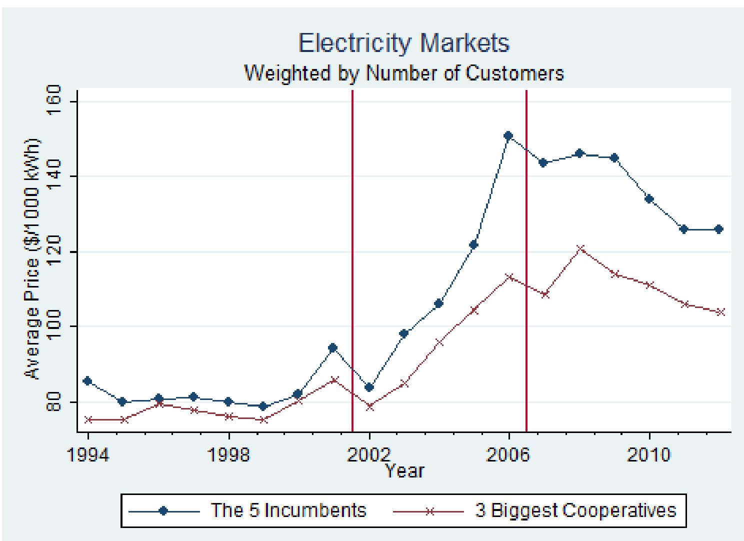
Notes: The figure above depicts, each year, the weighted average price of the five incumbents of the deregulated regions and the four regulated investor owned utilities not deregulated by Senate Bill 7. See Figure 1.3's notes for more details.

Figure 1.10: Average Price of 5 Incumbents, 5 Biggest Municipalities, 5 Biggest Controls



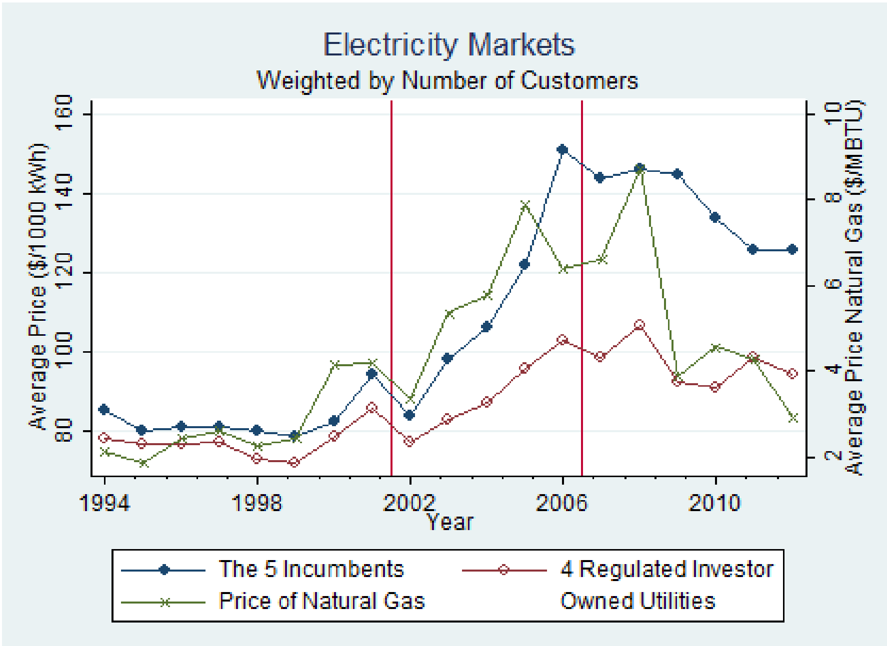
Notes: The figure above depicts, each year, the weighted average price of the five incumbents of the deregulated regions, the five biggest municipalities, and the five biggest controls (which includes 2 municipalities, 2 investor owned utilities, and 1 cooperative). See Figure 1.3's notes for more details.

Figure 1.11: Average Price of 5 Incumbents and 3 Largest Cooperatives



Notes: The figure above depicts, each year, the weighted average price of the five incumbents of the deregulated regions and the three biggest cooperatives. These 3 cooperatives are used in the final regression where results are depicted in column 6 of Tables 1.3 and 1.4. See Figure 1.3's notes for more details.

Figure 1.12: Average Price of 5 Incumbents, 4 Regulated Investor Owned Utilities, and the Price of Natural Gas



Notes: The figure above depicts, each year, the weighted average price of the five incumbents of the deregulated regions, the four regulated investor owned utilities not deregulated by Senate Bill 7, and the average price of natural gas. The price of natural gas is depicted on the right hand vertical axis. See Figure 1.3's notes for more details.

Table 1.1: Summary Statistics

Statistic of Interest	1999		2008	
	Deregulated/Treated Regions	Control Regions	Deregulated/Treated Regions	Control Regions
Number of Customers	4,586,127	3,235,662	5,408,468	3,979,997
Sales of Electricity (in 10 million kWh)	6.78	4.07	8.13	5.36
Average Price (in $/1000 kWh)	76.78	76.55	143.27	119.76
Number of Firms Classified as Municipalities	0	72	0	72
Number of Firms Classified as Cooperatives	0	72	0	66
Number of Regulated Investor Owned Utilities	5	4	0	4
Number of Deregulated Firms	0	0	45	0
Price Electricity Producers Pay for Natural Gas ($/MWH)	2.46		8.71	
Weighted Average Price of Coal, Nuclear, and Natural Gas	1.7		4.89	

Notes: The table above provides summary statistics from the primary data used in this paper, data from the Energy Information Administration, 2015. The statistic of interest is on the left hand side and the values in the corresponding years in the corresponding regions fill the next four columns.

Table 1.2: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results				
VARIABLES	1	2	3	4
	Using all regulated and deregulated firms			
Dereg * I_{2002}	14.169***	14.169***	14.459***	14.361***
	(1.036)	(1.022)	(1.066)	(1.062)
	[0.068]	[0.068]	[0.043]	[0.043]
Dereg * I_{2007}	9.160***	9.187***	9.293***	8.955***
	(1.325)	(1.337)	(1.336)	(1.326)
	[0.172]	[0.153]	[0.153]	[0.172]
Dereg	7.341***	7.341***		
	(2.632)	(2.636)		
I_{2002}	13.647***			
	(1.036)			
I_{2007}	12.832***			
	(1.325)			
Observations	3,196	3,196	3,196	3,196
R-squared	0.616	0.748	0.856	0.856
Controls	None	None	None	Quantity
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes
Mean of Dependent Variable, weighted = 96.43 (3.60)				

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in () are clustered at the region level (163 regions, 1 treated). Asterisks next to the coefficients are for p-values calculated using robust clustered standard errors. Conley-Taber p-values are expressed in [] for the variables of interest. This table uses all the deregulated firms and all the controls from 1994 to 2012.

Table 1.3: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results				
VARIABLES	(1)	(2)	(3)	(4)
	Using all regulated and deregulated firms			
Dereg * I_{2002}	-7.362***	-15.536***	-15.247***	-14.575***
	(2.183)	(2.111)	(2.215)	(2.134)
	[0.110]	[0.049]	[0.025]	[0.025]
Dereg * I_{2007}	25.164***	25.191***	25.616***	26.302***
	(2.679)	(2.684)	(2.680)	(2.719)
	[0.018]	[0.018]	[0.031]	[0.031]
Dereg	-2.281	5.892**		
	(2.634)	(2.916)		
I_{2002}	-14.461***			
	(2.183)			
I_{2007}	33.696***			
	(2.679)			
PNG*Dereg * I_{2002}	1.948***	4.893***	4.837***	4.648***
	(0.487)	(0.445)	(0.471)	(0.452)
	[0.172]	[0.018]	[0.006]	[0.006]
PNG*Dereg * I_{2007}	-2.478***	-2.482***	-2.538***	-2.748***
	(0.294)	(0.294)	(0.299)	(0.313)
	[0.012]	[0.018]	[0.012]	[0.012]
PNG* Dereg	3.466***	0.522	0.632	1.739***
	(0.000)	(0.369)	(0.403)	(0.588)
PNG*I_{2002}	4.885***			
	(0.487)			
PNG*I_{2007}	-3.484***			
	(0.294)			
Observations	3,196	3,196	3,196	3,196
R-squared	0.700	0.759	0.867	0.868
Controls	None	None	None	Quantity
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes
Mean of Dependent Variable, weighted = 96.43 (3.60)				

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in () are clustered at the region level (163 regions, 1 treated). Asterisks next to the coefficients are for p-values calculated using robust clustered standard errors. Conley-Taber p-values are expressed in [] for the variables of interest. This table uses all the deregulated firms and all the controls from 1994 to 2012.

Table 1.4: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results					
VARIABLES	1	2	3	4	5
Dereg * I_{2002}	15.288***	17.772***	17.495***	16.072***	17.047***
	(1.013)	(3.969)	(1.967)	(2.564)	(2.306)
	[0.080]	[0.009]	[0.001]	[0.004]	[0.001]
Dereg * I_{2007}	9.855***	17.463***	14.098***	15.799***	14.641***
	(1.400)	(3.651)	(1.878)	(2.823)	(2.310)
	[0.200]	[0.008]	[0.002]	[0.003]	[0.002]
Observations	1,794	171	190	190	323
R-squared	0.841	0.934	0.916	0.914	0.92
Control Clusters	74	4	5	5	12
Treated Clusters	1	5	5	5	5

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Standard errors are in (). Column 1 reports robust standard errors clustered at the region-level. Columns 2-5 report robust standard errors clustered at the company-level. Asterisks denoting significance are based on these standard errors. Conly-Taber p-values are reported in [] for column 1. Weighted bootstrap standard errors are reported in [] for columns 2-5 (1,000 times with replacement). Column 1 produces results from equation (1) using all firms in the deregulated regions and all municipalities. Columns 2-5 also produce results using equation (1) but use company, instead of region, fixed effects. In each of these regressions, the treated clusters are the five incumbents in the deregulated regions and all other firms in the deregulated regions are discarded. Column 2 uses the four regulated investor owned utilities as the controls. Column 3 uses the five biggest municipalities as the controls. Column 4 uses the five biggest controls. Column 5 uses the five biggest municipalities, four investor owned utilities, and three biggest cooperatives. This table uses all the years, from 1994 to 2012. All variables, but the variables of interest, are excluded for ease of readability.

Table 1.5: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results					
VARIABLES	1	2	3	4	5
Dereg * I_{2002}	-23.005***	-13.992**	-25.956***	-21.585***	-18.347***
	(1.618)	(4.452)	(3.302)	(4.051)	(4.256)
	[0.080]	[0.030]	[0.001]	[0.004]	[0.004]
Dereg * I_{2007}	26.769***	47.351***	42.403***	42.479***	42.079***
	(2.440)	(7.033)	(4.093)	(6.275)	(5.144)
	[0.067]	[0.000]	[0.000]	[0.001]	[0.000]
PNG*Dereg * I_{2002}	6.568***	5.189***	7.321***	6.355***	5.839***
	(0.299)	(1.259)	(1.074)	(1.156)	(1.149)
	[0.000]	[0.008]	[0.001]	[0.002]	[0.001]
PNG*Dereg * I_{2007}	-2.506***	-5.120***	-4.592***	-4.397***	-4.575***
	(0.287)	(0.845)	(0.675)	(0.861)	(0.741)
	[0.213]	[0.002]	[0.001]	[0.003]	[0.000]
Observations	1,794	171	190	190	323
R-squared	0.861	0.941	0.935	0.928	0.931
Control Colusters	74	4	5	5	12
Treated Clusters	1	5	5	5	5

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: This table follows the same format and structure as Table 1.4. See the notes for Table 1.4 for more details. All variables, but the variables of interest, are excluded for ease of readability.

Chapter 2: Labor Market and Health Insurance Effects of Missouri's Medicaid Contraction

1. Introduction

Does a contraction in public health insurance increase the labor supply? If so, is the increase focused among people seeking jobs offering employer-sponsored health insurance? The importance and implications resulting from changes in public health insurance has become an important topic as the Affordable Care Act evolves and expands. Taking advantage of a severe and sudden contraction in Missouri's Medicaid program, I estimate the effects on both labor supply and employer-sponsored health insurance and calculate a crowd-out estimate that occurs between public health insurance and employer-sponsored health insurance.

The labor supply effects of health insurance are of great importance to U.S. policy makers due to the implementation of the Affordable Care Act. Under the Act, many new families have access to public health insurance (PUHI). Understanding the effects of the implementation of a national health care plan is crucial to be able to prepare and plan for side-effects that might occur. While the Affordable Care Act is an expansion and Missouri's policy is a contraction, my estimates of crowd-out are similar to previous studies on both contractions and expansions, providing evidence that my labor supply and employer-sponsored health insurance (ESHI) estimates may apply, in opposite signs, to similar expansions.[44]

---

[44] Three similar estimates come from: Dubay/Kenney (1997), Yazici/Kaestner (2000), and Ham/Shore-Sheppard (2005).

In 2005, Missouri changed a few requirements to qualify for the state's Medicaid program. The key change studied in this paper is that parents who made more than 20% of the federal poverty level (FPL) no longer qualified for Medicaid (previously, the cutoff was more than 75%). This change led to over 90,000 parents losing Medicaid.[45] This paper investigates the questions proposed above by comparing the changes of parents in Missouri to a group of controls before and after the contraction.

Expectations of the sign and magnitude of the effects of PUHI on labor force participation and ESHI are ambiguous. Assuming people value PUHI, then adults who lose it might seek employment either by finding a job or increasing the number of hours they work. They might seek employment to gain ESHI or increase their working hours to earn more money to be able to pay for future medical expenses out of pocket. Losing PUHI could also result in decreased employment or number of hours worked. People might work less so they earn less money and meet the income thresholds to re-qualify for PUHI. People who lose PUHI might also experience deterioration in their health or an increase in disruptive health emergencies that might decrease their employment or number of hours worked. Since people could react by decreasing or increasing their earnings, which can be accomplished by increasing or decreasing one's labor supply, and there is conflicting evidence available to gauge which effect dominates, there is not one way we expect labor supply and ESHI to change. Finally, modeling the labor supply effects from a contraction in PUHI gives inconclusive results; therefore, empirical

[45] This value is calculated using data provided by the Missouri Foundation for Health.

strategies and estimations are necessary to arm policy makers with the proper knowledge for future actions. This paper does not test for the heterogeneous effects of the contraction but sheds light on the aggregate labor supply effects.

Taking advantage of both across- and within-state variation to the disenrollment, I use state-by-year-by-child status difference-in-difference-in-difference (DDD) analysis to compare the adults in Missouri with children before and after the contraction to adults in Missouri without children and to the adults in other states with and without children. This methodology allows me to identify the causal effect of the disenrollment on PUHI coverage, labor supply, and ESHI. I find that following Missouri's PUHI contraction and among parents with a high school diploma or less, there is a 5.4 percentage point decrease in PUHI, a 2.3 percentage point increase in employment, a 1.1 percentage point increase in parents seeking part time work, and a statistically insignificant 3.7 percentage point increase in ESHI. This paper confirms the robustness of these results by using different sets of controls, using adults with different levels of education, narrowing in on adults with lower income levels, and performing state falsification tests. These robustness and falsification tests support large and significant effects from the PUHI contraction on parents seeking employment and seeking it in part time work.

My results build on a large body of literature studying labor supply and ESHI effects resulting from Medicaid policies. The results from this body of literature have some common and some mixed results. Gruber (2000) and Gruber and Madrian (2002) provide an overview of the empirical studies on the effects of health insurance on labor supply in the US. They explain that many of the studies they review have problematic identification strategies. The identification problems in the papers they review arise because of the collinearity of Medicaid and Aid to Families with Dependent Children; the independent relationship between health status on welfare and labor supply; the noisy measure of the underlying value of Medicaid to potential recipients resulting in attenuation bias; the probable reverse causality between labor force participation decisions and variation in state Medicaid expenditures; and/or to assuming that a husband's ESHI is exogenous. Ignoring these identification problems, the papers they review generally agree that health insurance has no labor supply effect on low income mothers, but does affect labor force participation and job choice for possible retirees and secondary earners. In contrast to these conclusions, Yellowitz (1995) finds that increasing Medicaid's income limit increases the labor force participation of divorced and separated, but not never-married, women. The identification strategy I use, across- and within-state variation, improves on these earlier papers.

In more recent studies, Decker and Selck (2012) and Strumpf (2011), both using datasets from the 1960's and 1970's, find no impact from Medicaid on the labor force participation of women. Baicker et al. (2013), using OLS and 2SLS examine the employment effects of Oregon’s PUHI lottery and find small and statistically insignificant changes in labor market outcomes (employment, earnings, or earnings above the FPL). Azuara and Marinescu (2011), Barros (2008), and Campos-Vazquez and Knox (2013), using a difference-in-difference approach, study the employment effects of

Mexico's Seguro Popular program--a national free or subsidized health insurance program. All three find no impact of Seguro Popular on employment outcomes. Garthwaite, Gross, and Notowidigdo (2014) (GGN), using the same causal identification strategy I use, study the effects of a PUHI contraction in Tennessee on labor supply and ESHI. They find labor supply increases in response to a loss in PUHI and that the increase is concentrated among individuals working more than 20 hours each week and seeking ESHI.

This paper contributes to the health insurance employment literature in many ways. First, I study Missouri, a state previously unstudied which includes a different group of adults than prior literature has focused on (my paper focuses on all low income parents rather than just single mothers or more affluent parents). Second, I utilize the American Community Survey, which provides a larger sample than many previous papers and, therefore, more precise results on employment information, adding to the validity of my conclusions and estimates. Third, using data from a contraction that occurred in 2005, I provide more recent estimates of Medicaid's effect on labor supply and ESHI than most papers. Additionally, due to the nature of Missouri's contraction, I can focus on the effects of all low income parents rather than just single mothers (like many previous studies). Due to focusing on all low income parents, my study provides the most accurate estimates of employment effects we can expect to see from the Medicaid expansion portion of the Affordable Care Act. Finally, I perform additional robustness checks and falsification tests not done in previous papers that lend validity to the causal interpretation given in this paper. Combining the above, I am able to provide more recent and precise estimates of PUHI effects on labor supply, hours worked, and ESHI than many previous studies. My paper provides support for GGN's results and counters those found by Baicker, et al. (2013) and the economists mentioned above who studied Seguro Popular.[46]

This paper proceeds as follows. Section 2 gives the relevant background on Missouri's health care reform. Section 3 builds a basic labor supply model and shows theoretical predictions. Section 4 explains the primary data sets used, details how I narrow in on the observations used in the study, and gives the empirical strategy. Section 5 provides the empirical analysis and results. Section 6 provides robustness checks and falsification tests. Section 7 concludes.

2. Missouri's Health Care Reform

In 2005, the Missouri Legislature enacted Missouri Senate Bill 539 (MFH, 2008). The bill was introduced on March 1, 2005 and signed by the Governor on April 26, 2005 (Missouri Senate, 2015).[47] This bill decreased the income level required to qualify for the state's Medicaid program. Letters were sent to families starting in late April 2005 and actual disenrollment began in July 2005, continuing through the middle of 2006

[46] The difference might be because the latter two study expansions of PUHI while mine studies a contraction, which is also what GGN study. People's reaction to an expansion might not be symmetric to a contraction.

[47] The bill was an exogenous shock to the Medicaid recipients. The first mention of the tightening of the Medicaid income limit came about on January 20, 2005 when Governor Blunt talked about the need to reform Medicaid in his State of the State address (Barker, 2015). Prior to the address, there was no media attention or any other reason to believe that Medicaid was going to be contracted.   Following the address, discussion of the contraction was limited to advocates of Medicaid and health care personnel. Ryan Barker, Vice President of Health Policy, *Missouri Foundation for Health,* stated that the vast majority of people who were going to lose Medicaid were unaware of the change until they got the letter in the mail.

(Barker, 2014). The contraction led to almost 180,000 people losing Medicaid coverage, with the majority having lost it by the end of 2005. Table 2.1 depicts the income guideline changes that took place after the contraction in Missouri's PUHI program. Column 1 gives the covered population, column 2 gives the income guidelines prior to the contraction, and column 3 gives the new/current income guidelines to qualify for Medicaid. As shown in Table 2.1, parents no longer qualify for Medicaid unless they made ≤ 20% of the FPL (previously it was < 75% of the FPL). Children, pregnant women, and blind individuals had no changes to their income guidelines. [48]

Table 2.2 puts the percentage changes into context of actual dollars. The first column lists the number of members in a household. The next 6 columns give the dollar amounts equal to the corresponding percentage of the FPL labeled at the top of the column. In 2005, a family of four who made 75% of the FPL earned $14,513 (USDHHS, 2015). A family of four at 20% of the FPL earned $3,870. Clearly, this change affects many of the lowest earning income families.

Figure 2.1 shows a graphical depiction of the effect of the disenrollment. The graph is created using data provided by *The Missouri Foundation of Health*, the state's public health care provider. Year is on the horizontal axis. The total enrolled in Medicaid is on the left vertical axis and the enrolled adults/custodial parents are on the right vertical axis. The blue, plus marked line depicts the total number of people on Medicaid.

[48] Disabled and Elderly Adults (age 65+) were also impacted. The income guideline changes for them went from < 100% FPL to < 85% FPL in order to qualify for Medicaid. Thus, any disabled or elderly adults on Medicaid making between 85% and 100% of the FPL lost it. They were omitted from the table to avoid distracting the reader with other changes not applicable to this paper. These changes offer a possible area for future research.

The red, triangle marked like depicts the adults on Medicaid. The green, square marked line depicts the custodial parents on Medicaid. The red, vertical line depicts the implementation of the Medicaid contraction, in July of 2005. The figure shows that approximately 170,000 people (90,000 adults/custodial parents) lost insurance following the contraction.[49] Adults were reclassified as custodial parents in April 2005 to distinguish that only adults with children receive Medicaid. Prior to 2005, they were labeled adults but really should have been labeled parents since, in Missouri, only adults with children have ever been able to qualify for Medicaid. When the adults were reclassified as custodial parents, pregnant women were added to this category. Thus, the absolute drop in magnitude of these two categories is nearly identical since pregnant women did not have any change to their income requirements following the 2005 contraction (as shown in Table 2.1). I take advantage of this exogenous shock to Missouri's Medicaid program to study the effects on labor supply and ESHI among parents. I use the fact that parents in Missouri were the only adults impacted as two of the three parts of my identification strategy (time is the final part).

The astute reader may wonder why the decrease seems to begin right before July of 2005 instead of right after it. Employees of Missouri's Medicaid program were well aware of the changes that were going to take place in July 2005 and the time it would

[49] For a complete description about the disenrollment, please refer to Ferber et al. (2005), Chase et al. (2008), and Zuckerman et al. (2009). 180,000 total people lost Medicaid but pregnant women experienced an increase of 10,000 enrollees during this timeframe, resulting in the figure's depiction of 170,000 losing Medicaid. The other 90,000 people who lost Medicaid during the contraction includes approximately 67,000 children moved from Medicaid to other public health insurance programs, 4,000 elderly, and 19,000 disabled people. More detailed information is available upon request.

require them to disenroll all the parents who no longer qualified for Medicaid. Thus, in April 2005, they began going through the records and disenrolling any adults who were still on Medicaid but making ≥ 75% of the FPL (and thus should not be on Medicaid according to Missouri's standards even prior to the contraction) (Barker, 2014).

The setting and variation I take advantage of in this paper is very similar to GGN's paper. Like GGN, I study the effects of a PUHI contraction using a DDD approach. While similar in many ways to their paper, there are a few major differences. One is that they study a policy that took place in Tennessee while I study a policy in Missouri. In contrast to their study focusing on childless adults making ≤ 400% of the FPL, the people affected in Missouri are very poor parents making between 20% and 75% of the FPL. My study is, arguably, the most applicable estimate to understanding the effects of the Medicaid expansion portion we will see from the Affordable Care Act. With the Affordable Care Act, all adults making ≤ 133% of the FPL will be able to enroll in Medicaid (Medicaid.gov, 2015). The policy I study affects a subset of this group (parents making 20% to 75% of the FPL); therefore, it is more representative of the effects we will see from this group than GGN's paper. Another difference is that I use a newer and larger data set for employment information, the American Community Survey. Finally, I perform some additional robustness checks and falsification tests that support the causal interpretation resulting from a contraction in PUHI.[50]

[50] It would be interesting to perform these robustness and falsification tests on GGN's results.

While the dependent variables of interest are similar, this study is very different from Baicker et al.'s (2013) in two important ways. First, they study an expansion while I study a contraction. Second, they study the effects in Oregon, while I study effects in Missouri. This difference gives my study more credibility in effects we might see from the Affordable Care Act. When looking at age, race, education levels for people with a high school degree or less, and population below poverty level, the state of Missouri is much more representative of the United States than the state of Oregon.[51]

3. Model

To align expectations on the effects from Missouri's Medicaid contraction on labor supply, I modify and combine the model given in Yellowitz (1995) and Bitler et al. (2006) to develop a basic labor supply model of a household, defined as having 2 adults capable of working. The model I use depicts values using Missouri's Medicaid contraction. I use a variant of the static labor supply model by incorporating taxes and make conventional economic assumptions--the household maximizes their concave utility, U = u(c,l), and consumption and leisure are normal goods. The household faces a constant pretax wage ω^0 and after tax wage $\omega^1 = (1-\tau^0)*\omega^0$.

Figure 2.2 shows a stylized budget constraint in the income-leisure space faced by all households in Missouri. Prior to the contraction, the budget constraint faced by a household was the line connecting AEGBD. Line AE represents the consumer's value of Medicaid. The discontinuous drop in benefits, line BG, is known as the "Medicaid

51 Basic demographic data from the U.S. Census Bureau (2015) for Oregon and Missouri was compared to the United States overall to make this claim.

notch" and creates a dominated part of the budget set represented by line BC (point C is perpendicular to point G). In such a situation, as was the case prior to Missouri's 2005 contraction, households will locate on line EG or CD since AC is strictly dominated by EG. We expect bunching to occur at point G.

After the contraction, all households now face the budget constraint AEJHD. Using the same logic as above, all households now locate on line EJ or KD since AK is strictly dominated by EJ (point K is perpendicular to point J). The labor response is ambiguous. Households who originally located between points [E, J] and [C, D] will stay at the same position (since options have not improved) but households who located between (J, G] will be forced to move. Depending on their preferences (represented by an indifference curve), the households between (J, G] will either move to a new bunching point J or move to somewhere on [K,D]. If they move to point J, they will have decreased their employment, either by a member of the household quitting or decreasing the number of hours they work. If the new location puts them on line KD then they will have increased their employment (intensively or extensively). Since the labor response is ambiguous, we need to turn to empirics to determine the results.

The table in Figure 2.2 summarizes the above paragraph and the different movements that could happen. The left column depicts a point where the household might have located prior to the contraction. The right column depicts where that household would move to, given they started on the corresponding row in the left column.

The indifference curves depicted in Figure 2.2 represent one way a household might have reacted, and are drawn to illustrate what I find in the Missouri data. Given that people in Missouri lost PUHI and that employment increased, households might have moved from point G to point L, as depicted. The indifference curve depicted, Curve^1, depicts a household who originally located at point G before the contraction in Missouri (where we expected to see bunching). After the contraction, Curve^2 represents the optimal tangency point where this household maximizes their utility--by locating at point L. This type of move has the household increasing their labor supply since they are decreasing their leisure.

4. Data and Empirical Strategy

4.1. Data

For this research, I use the Integrated Public Use Microdata Series (IPUMS) to gather data from the Current Population Survey (CPS). Specifically, I use the CPS March supplemental surveys from the years 2000 to 2008 as they contain additional information on income, poverty, and health insurance. Since the state of Missouri provides Medicaid for qualified children under the age of 19, I classify adults as those who are ≥ 19 years old and remove anyone who is not an adult from the dataset.[52] To prevent confounding my results with evidence from Medicare or Tricare (the military's health insurance plan) and to mitigate the survey response errors, I remove anyone over

[52] In principle, I should also eliminate pregnant women, blind individuals, and retired veterans who may be eligible for Tricare. I do not see that information in my data and I also assume those groups that are interviewed are very small. By not eliminating them from the data, I am biasing my results to finding no effect.

the age of 64 and anyone serving in the military. To keep most of the observations but narrow my focus on the affected group, I restrict the sample to adults with a high school diploma or less.[53] Restricting on income probably focuses on the group of interest more accurately than restricting by education, but potentially selects on the outcome. Since my data is cross sectional and not panel and I want to avoid this endogeneity issue, I instead restrict the sample by education.[54] In order to avoid the effects of the 2008 recession, I run regressions using the years 2000 to 2007, giving me 6 years of data before the contraction and 2 years after it.

The health insurance questions that pertain to the years 2000 to 2007 come from the 2001 to 2008 March CPS surveys because health insurance questions ask about coverage in the previous year. I use the health insurance sample weights from the CPS for the health insurance variables in all but the non-weighted regressions.[55] I classify individuals as having PUHI if they claim to have any type of public health insurance.[56] I classify individuals as having employer sponsored health insurance if they claim to have insurance through their employer.

---

[53] Robustness checks with adults having different levels of education are performed and discussed in the robustness section.

[54] Approximately 65% (4%) of the people who make between 20% and 75% of the FPL have a high school diploma or less (bachelor's degree). More detailed numbers and data focusing in on these income groups and education levels are available upon request. Robustness checks using income level restrictions are displayed and discussed in the robustness section.

[55] While not shown, regressions not weighted are available upon request. Results are similar to the weighted regressions.

[56] I classify PUHI in this way as opposed to those on Medicaid because many states have names for their Medicaid program. For example, Missouri calls their program MOHealthNet, Tennessee calls theirs TennCare, and Oklahoma calls theirs SoonerCare. Thus, in a survey, someone might claim to have PUHI but not Medicaid, even though they do. Since I have eliminated all military personnel and people 65 or older, I have effectively eliminated anyone with Tricare or Medicare – except those who are disabled. The few people I am picking up under these two programs or other PUHI programs by classifying as I have creates a trivial, if any, amount of noise.

The employment information comes from the 2000 to 2007 March CPS surveys and pertains to the survey reference week. I classify someone as working if they are at work during the survey reference week and use the number of hours they report being at work during that week for my hours calculations. Thus, all hours calculations are conditional on being employed and pertain to the survey reference week. For all non-health insurance outcomes, I use the person-level weights from the CPS supplement.

Table 2.3 presents summary statistics for the group that is left in MO from 2000-2007. The second column, labeled “Missouri,” includes the sample in Missouri before the education restriction is enforced. “45” includes DC and the other 44 states that did not have a contraction in their public health insurance at the same time as Missouri (the 5 states omitted include Tennessee, Oregon, Utah, Ohio, and Connecticut). While all 45 regions are not truly states (one is DC), I will refer to this control group as the 45 states from now on. The third column, labeled “45”, includes the sample in the 45 states no matter the level of education of the adults. The fourth column, labeled “Diff”, represents the difference between the average percentage in Missouri and the average percentage in the 45 states. Columns 5-7 follow the same format as above but represent the group that is left after removing anyone with more than a high school diploma. Within this group, Missouri, when compared to the 45 states, appears to have a greater percentage of people with private health insurance, a greater percentage of white adults, and a greater percentage of high school graduates (and thus smaller percentage of high school dropouts). All other values are very similar.

I also use the IPUMS to gather data from the American Community Survey (ACS). I perform the same restrictions described above with the CPS to focus in on my population of interest. The ACS has many more observations but does not provide health insurance information until 2008 and thus only helps my study for employment information. The employment variables in the ACS are slightly different than in the CPS. Instead of all employment information being related to the reference survey week, it pertains to the past calendar year from the day of the survey. The survey can be given anytime throughout the year. I use the years 2000 to 2007 to match up with the CPS years used.[57] In the ACS data, I also gather the weeks worked and can condition it on being employed (and thus obtain an intensive response) or not condition it at all (and thus obtain an intensive + extensive response). This proves helpful when trying to determine and provide support for extensive and/or intensive employment responses.

Table 2.4 follows the same format as Table 2.3 but uses the ACS data instead of the CPS data; therefore, it uses the surveys from 2001 to 2008 to capture the information from 2000 to 2007. In this data set, the only notable differences are the race percentages. Missouri appears to have more white adults and fewer "other" adults, compared to the other 45 states. Comparing the ACS to the CPS, percentages are roughly equal.

4.2. Empirical Strategy

I take advantage of the across- and within-state variation that occurred from an exogenous shock in Missouri's Medicaid contraction in 2005 when 180,000 people,

[57] I also run regressions using through 2008 or changing the year of implementation to be 2005 and 2007. Results are similar to what is shown in the next section and are available upon request.

90,000 parents, were disenrolled from Medicaid. I use a DDD regression to make my causal conclusion--a contraction of PUHI leads to an increase in labor supply and among people seeking part time work. The results are suggestive in nature that individuals seek out employment among jobs offering ESHI and that a large crowd-out between PUHI and ESHI exists. Further, the increase in labor supply appears to be predominantly along the extensive margin.

I perform many DDD regressions after aggregating at the state-year-child level without any control variables to highlight that the statistical significance of my results do not depend on including individual-level covariates.[58] I exploit the fact that Missouri had a contraction in the middle of 2005 that affected poor adults who had children. My aggregate DDD regression takes the following form:

$$y_{stk} = \alpha_s + \alpha_t + \alpha_k + \gamma_{st} + \gamma_{sk} + \gamma_{kt} + \beta * \mathbb{1}_{s=MO} * \mathbb{1}_{t\geq 2006} * \mathbb{1}_{k=1} + \epsilon_{stk}. \quad (1)$$

y_{stk} is the outcome of interest in state *s* at year *t* with child status *k* (which is equal to 1 if the adults have a child and 0 if the adults do not). α_s are state fixed effects, α_t are year fixed effects, and α_k are child fixed effects. γ_{st} are all the state-time pairwise interactions, γ_{sk} are all the state-child pairwise interactions, and γ_{kt} are all the child-time pairwise interactions. The indicator variable $\mathbb{1}_{s=MO}$ takes on a value of 1 if the state is Missouri (which is the treatment group) and 0 otherwise. The indicator variable $\mathbb{1}_{t\geq 2006}$ takes on a value of 1 if the year is 2006 or greater and 0 otherwise (to capture post implementation). The indicator variable $\mathbb{1}_{k=1}$ takes on a value of 1 if the adults have

[58] Results with covariates included in the regressions are very similar to without. Results are available upon request.

children and 0 otherwise. The error term ϵ_{stk} accounts for the effect of all unobserved variables which vary over state, time, and child status and is assumed to be uncorrelated with all observables. The parameter of interest is β. β identifies the impact of the contraction on the outcome variable. A value of $\beta = 0.05$ would be interpreted as follows: a 5 percentage point change for adults in Missouri with children relative to adults in Missouri without children as well as adults in other states with and without children.[59]

This DDD regression controls for any unobservable common shocks that affected all parents across the country in a given year as well as all unobservable shocks that affected all adults in Missouri in a given year. The key identifying assumption for the DDD is that outcomes for adults with children in Missouri would have evolved in a similar fashion to the outcomes of other adults without children in Missouri relative to adults with and without children in other states, absent Missouri's contraction. Using the DDD specification allows me to address the concern that Missouri would have evolved differently than other states even in the absence of the disenrollment and that parents would have evolved different than childless adults, absent the contraction. Finally, it allows me to address the concern that outcomes for adults with and without children might have varied across states, absent the contraction.

The main 3 outcomes of interest (dependent variables) are share of people with public health insurance (PUHI), employed, and employed with employer-sponsored

[59] For ease of reading, I will not refer to this interpretation every time but will instead just state the percentage point change. However, I always mean relative to the interpretation just described.

private health insurance (ESHI). In order to add support for people seeking out ESHI, the other 4 outcomes of interest are share of people working < 20 hours/week (to see if people transition to working part-time), working ≥ 20 hours/week (to see if people transition to working more than part time), working 20-35 hours/week, and working ≥ 35 hours/week (to see if people transition to full time jobs). If people seek out more than part-time work then they are more likely to obtain ESHI, though some part-time jobs do provide ESHI. Due to the contraction, I expect β to be negative for PUHI but, as explained in the introduction and model section, do not have expectations for its sign or magnitude when the dependent variable is employment or ESHI.

One might prefer the use of the exact people the contraction targeted, parents with incomes in the range of 20-75% of the FPL, or making less than or equal to a certain level of income. Both data sets I use are cross-sectional, not panel. Thus, I am not following people through time. Targeting the exact income group affected might have an endogeneity problem due to a selection issue as many of the treated people who lose PUHI might gain employment and move above the 75% income level or might move below the 20% level to re-qualify for PUHI and would thus drop out of my data. There might be reverse causality if I condition on an income level since this is arguably like conditioning on the outcome variable. As robustness checks, I perform the DDD after conditioning on income levels instead of education levels. Results are discussed in the robustness section and follow the pattern we would expect (larger effects as I narrow in on the income level).

One challenge in estimating equation (1) concerns statistical inference. My baseline sample includes DC and 45 states observed over an 8 year period and the main regressions are run on state-year-child means computed from individual-level data. Therefore, I need to compute standard errors that account for serial correlation within states over time and sampling error in cell means. A common approach is to use cluster-robust or block-bootstrap standard errors (Bertrand, Duflo, and Mullainathan, 2004). However, when these procedures are carried out on aggregate data, they do not explicitly account for sampling error in cell means and may therefore not be accurate in small samples (GGN, 2014). For this reason, I estimate standard errors using a modified two-stage block bootstrap procedure that is commonly used in statistics literature in the analysis of survey data (Rao and Wu, 1988).

The modified two-stage block bootstrap procedure entails two parts. First, I re-sample the states, with replacement. If the sample does not include Missouri, I discard the draw. If the sample includes Missouri, I sample the individual level data within each state (with independent re-sampling for each state cluster chosen more than once). I then calculate the cell means for each state-year-child status for this bootstrap sample and estimate equation (1). I repeat this procedure 800 times and then compute the standard error of the point estimates across these replications and use this as the two-stage block bootstrap standard error estimate reported in the tables.

5. Empirical Results

In this section I present the main empirical results. Using the CPS data, I first show how the Missouri disenrollment affected PUHI coverage and is suggestive of an employment increase and increase amongst those employed with ESHI. I then examine the changes in the labor supply that occur using the ACS data for more precise results, which provides conclusive evidence that employment increases and most of the increase is amongst laborers finding part time employment. Finally, I present estimates of the crowd-out of ESHI resulting from PUHI based on my findings.

5.1. Effects on Health Insurance

Figure 2.3 presents the share of residents who report having PUHI. Share covered by PUHI is on the vertical axis and two-year binned means are on the horizontal axis (given the small cell sizes, I group the respondents into two-year bins in the figures but run all regressions with years individually). The green, big X marked line displays the adult population in Missouri with children (the treated group). The blue, big square marked line depicts the adult population in Missouri without children. The red, small square marked line displays the adults in the 45 states without children. The orange, small x marked line displays the adults with children in the 45 states. As expected, there is a noticeable negative break in the trend of PUHI following the 2005 contraction for parents in Missouri. While the line displaying parents with children in Missouri is not parallel to the other 3 lines, there is a steady increase in two of the other three lines, and a clear break and reversal of this trend for Missouri. The drastic change is not noticeable in the other 3 groups; in fact, they remain relatively stable through the break.[60]

Table 2.5 presents regression estimates of equation (1) using data from the CPS. Each column in the table represents a different regression according to equation (1), with the different dependent variables listed in the top row of each column. Each row gives the statistics listed on the left hand side of the table for the dependent variable labeled at the top of the column.[61] As described earlier, two-stage block bootstrapped standard errors are reported.

Column 1 of Table 2.5 presents the estimates for share covered by PUHI. Parents in Missouri experience a 5.37 percentage point decrease in PUHI, relative to the other groups. Statistically significant at the 5% level and taking into account the mean of the share with public health insurance, this change translates into more than a 32% decrease in public health insurance; which roughly lines up with Figures 2.1 and 2.3.

Figure 2.4 presents the share of residents who report being employed with employer sponsored health insurance. Except for the change of the variable on the vertical axis (now it is the share employed with ESHI) the format is the same as Figure 2.3. There is a clear downward trend with all 4 groups prior to the contraction but, again, the line displaying the parents in Missouri breaks this trend and reverses sign following

[60] The sharp increase in Missouri adults without children from the 2002-2003 period to the 2004-2005 period is a concern. While my main analysis uses the years from 2000 to 2007, analysis was also done changing the years to only include 2004 to 2007. The results using the shorter pre period support my main results presented in this paper and the choice of a longer time period. Additional information and details are available upon request.

[61] All variables but the variable of interest are excluded for ease of readability.

the contraction. The other three groups all continue the same trend through the contraction. Only parents in Missouri see the drastic increase in ESHI following 2005.

Table 2.5, column 7 depicts regression estimates of equation (1) for the share employed with ESHI. The equation estimates there to be a 3.71 percentage point increase among parents in Missouri with ESHI. This value is statistically insignificant though and it cannot be rejected that the value equals 0. Therefore, the value is merely suggestive and interpretation of the coefficient should be done with caution. Taking into account the mean of the dependent variable, a 3.71 percentage point increase equates into almost a 6.4% increase among parents in Missouri with a high school diploma or less obtaining ESHI.[62]

5.2. Effects on Labor Supply

Figure 2.5 uses the CPS data to display the share of residents employed. The format is the same as Figures 2.3 and 2.4. The only difference is that the vertical axis now represents the share employed. As in the other two figures, there is a noticeable break following the contraction among parents in Missouri. The four groups follow the same basic trend prior to the contraction. All four increase employment following 2005 but Missouri increases employment at a greater rate than the other three groups.

Table 2.5, column 2 depicts regression estimates of equation (1) for the share employed. While the coefficient is an economically significant 1.9 percentage point

---

[62] It might be a concern that some other event may have happened around the same time as the contraction that led to parents in Missouri gaining ESHI, such as marrying someone for this purpose. Running regression equation (1) with "being married" as the dependent variable reveals that people were not marrying to gain ESHI. Using the ACS data and "being married" as the dependent variable results in a $\beta = 0.006$ with a standard error of 0.009.

increase, it is imprecisely estimated and not statistically significant. Thus, it is merely suggestive of employment increases but by no means conclusive. The coefficients for working ≥ 20 hours/week (column 4) and 20-35 hours /week (column 5) suggest an increase towards more than part time employment and, therefore, jobs with ESHI but are not statistically significant.[63]

To improve the precision of the estimates, I now turn to regression results using the ACS data.[64] Table 2.6 displays these results and follows the same format as Table 2.5. The coefficient in column 1, share employed, shows there to be a 2.3 percentage point increase in employment amongst the parents in Missouri, relative to the controls. Comparing this to the mean, we see employment increased over 3% for parents in Missouri. Of this group, it appears almost half of them began working < 20 hours/week. A statistically significant 1.1 percentage point increase equates to a 43% increase in working < 20 hrs/week, conditional on being employed. While employed and working ≥ 20 hours/week is similar in magnitude on a percentage point basis as working < 20 hours/week, it is much smaller on a percentage basis. Taking into account the mean of the dependent variable, a 1.21 percentage point change equates to approximately a 1.8% change in employed and working ≥ 20 hours/week. Such a low percent change, along with the fact that it is not statistically significant, prevents any conclusive statements from being made about more than part time work. While these results using the ACS

[63] Pictures depicting the trends for the other 4 dependent variables in this table are available upon request.
[64] Pictures depicting the trends for the 7 dependent variables studied using the ACS data are available upon request.

data are suggestive that people are seeking part time and full time work, only part time work is statistically significant.

Of the coefficients in columns 3-7, only the one in column 7 is both economically and statistically significant. The coefficients in columns 6 and 7 are not percentage point changes like the other coefficients in the table. The coefficients in these two columns represent the change in weeks worked. Column 6 displays results for weeks worked along the intensive margin (i.e. weeks worked conditional on being employed). Column 7 displays the results for weeks worked, without any conditioning. Therefore, it represents the extensive plus intensive weeks worked. Analyzing the extensive plus intensive weeks worked coefficient in column 7 reveals a significant change, at the 5% level. The extensive plus intensive weeks worked increases 0.89 weeks for parents in Missouri, relative to the controls, which equates to more than a 2.5% increase in weeks worked. This is in stark contrast to the coefficient for intensive weeks worked (shown in column 6). The economically and statistically significant coefficients for employment and extensive plus intensive weeks worked, combined with the economically and statistically insignificant value of intensive weeks worked suggest that people who lost their PUHI sought out employment along the extensive margin, not the intensive one. The fact that we see an increase in employment and those employed and working < 20 hours/week, combined with the economically small and/or statistically insignificant values for employed and working ≥ 20 hours/week, employed and working 20-35 hours/week, and employed and working $\geq$ 35 hours/week all suggest that people are entering the labor force and finding part time jobs.

While some part time jobs do offer health insurance, it seems that many people are entering the labor force to earn money, but not necessarily to gain ESHI. While the CPS data shows employed with ESHI to be economically significant but statistically insignificant, the results using the ACS data indicate that, in contrast to those results, people may in fact be seeking employment but not employment with ESHI. Providing further support for the suggestive CPS results that people are seeking out employment with ESHI is that the 95% confidence intervals for employed with ESHI (table 2.5, column 7) and employed and working $\geq$ 35 hours/week (table 2.6, column 5) are not inconsistent with each other. Since the confidence intervals overlap, I cannot reject that the numbers are not statistically the same.

Analyzing Tables 2.5 and 2.6 simultaneously, and utilizing information from the U.S. Census Bureau reveals greater insight. In 2005, approximately 5,800,000 people lived in Missouri, of which 4,420,000 were 18 years or older (U.S. Census Bureau, 2015). Using the summary statistics from the ACS in Table 2.4, almost 46% of those people have children and almost 49% of the people have better than a high school diploma. Assuming these characteristics are evenly dispersed, this equates to almost 1,000,000 people in Missouri being 18 years or older, having a child, and having a high school diploma or less (the only difference between this group and the group studied in this paper is that I do not include 18 year olds in the adult population). Column 1 of

Table 2.6 depicts the mean employment rate amongst this group to be 68.11%. The increase of 2.31 percentage points translates into approximately a 3.3% increase in employment and in 23,100 parents in Missouri with a high school diploma or less finding employment during the two years following Missouri's contraction. The estimate from Table 2.5, column 7 suggests an increase of approximately 3.71 percentage points amongst those employed with ESHI. This equates to approximately a 6.4% increase in the mean employed with ESHI rate and suggests that 37,100 parents in this group gained employment with ESHI. The fact that more parents in this group gained employment with ESHI than simply gained employment leads to the suggestive conclusion that people may not only enter into employment to find ESHI but may also increase their hours in their current job to gain ESHI or switch from their job without ESHI to one that offers ESHI. These estimates and empirical methodology all lead to the causal interpretation that people who lose PUHI seek out employment and some may seek out ESHI.

These results are similar in sign and significance to GGN's results but smaller in magnitude. The magnitude differences are likely due to the fact that the two contractions affected different groups of people (Tennessee's affected wealthier childless adults who made ≤ 400% of the FPL while Missouri's affected poorer parents in Missouri who made 20%-75% of the FPL). Since the effected group in Missouri makes less money in general, it is possible a greater percentage of the Missourian adults who lose PUHI lack the necessary qualifications to gain full time employment and employment with ESHI. The similarity in sign and significance are likely because we both study contractions.

The similarity also supports both papers' results -- the people who lose PUHI seem to react by seeking employment and some seek employment with ESHI.

Table 2.7 depicts the crowd-out estimate and the parameters used to calculate it. With the exception of the last column, the format of this table is the same as the prior two tables. Columns 1 to 3 are values pulled from the previous two tables and are presented again here for ease of reading. Column 4 presents the crowd-out estimate of ESHI resulting from PUHI. The crowd-out of ESHI resulting from public health insurance is apparent. Dividing the coefficient of employed with ESHI by the coefficient for having PUHI, $\frac{\beta_{ESHI}}{\beta_{AnyPublic}}$, results in a crowd-out of 69%. However, the value is extremely imprecise; therefore, it is only suggestive in nature and clearly it cannot be rejected that the coefficient is equal to 0. My estimate of the crowd-out is close to GGN's estimate (they calculate a crowd-out of 57%). This could be because the estimate is actually 0 (and thus it is smaller than GGN's estimate, which then lines up with the above discussion about the differences between our two populations) or because many of the people in my study increased their hours in the same job to gain ESHI or switched from a job that did not offer ESHI to one that did.

The statistical insignificance of my crowd-out estimate lines up with many prior studies that study PUHI expansions effecting people who make below the poverty level, which is the group of people affected in Missouri's contraction. Specifically, the imprecision of the results that prevents me from being able to reject that the value may equal 0 lines up with Aizer and Grogger (2003), Card and Shore-Sheppard (2004), Shore-

Sheppard (2005), and Ham and Shore-Sheppard (2005). The symmetry I find in my contraction to these studies analyzing expansions is interesting and provides suggestive evidence that my labor supply estimates may also imply a similar symmetrical response to similar expansions.

6. Robustness Checks and Falsification Tests

In this section, I present multiple robustness checks and falsification tests that provide support to my estimates. I first perform the same DDD analysis as done in the previous section on the states that border Missouri as opposed to the 45 states. I then test the heterogeneity of the results on adults with different levels of education. Following this, I test each data set without any education restrictions but instead condition on adults by income level. Additionally, I calculate crowd-out estimates when performing all of the robustness tests mentioned above to create a range of possible crowd-out estimates. Finally, I perform state falsification tests on the variables that are statistically significant in the main analysis to see if other states would give similar results that would cast doubt on the estimates presented in the previous section. Performing these state falsification tests allow for an alternative approach to inference.

6.1. Robustness Check Using Border States

Table 2.8 presents regression results of equation (1) using the states that border Missouri instead of the 45 states.[65] Panel A depicts regression results using the CPS data and follows the same format as Table 2.5. Panel B depicts results using the ACS data

[65] I do not include Tennessee since they had a major contraction at the same time. I include Indiana, despite her not actually touching Missouri, because she is very close in proximity to Missouri.

and follows the same format as Table 2.6. Overall, results are very similar in magnitude and significance to the main results presented in Tables 2.5 and 2.6. In panel A, the sign and magnitude of the coefficients for having PUHI, being employed, and being employed with ESHI are almost identical to the main results. However, the significance for having PUHI decreases (the p-value is < 0.1). The three variables that were significant in the main analysis using the ACS data: employed, employed and working < 20 hours/week, and the extensive plus intensive weeks worked are still significant in the regression using only the states bordering Missouri, though slightly less significant. The signs and magnitudes of these coefficients are almost identical to the main results. The similarity in these estimates provides robustness to the main results presented in Tables 2.5 and 2.6.

6.2. Robustness Check Using Different Education Levels

Table 2.9 follows the same format as Table 2.5 but includes only adults who are high school dropouts (in panel A) and only adults with more than a high school diploma (in panel B). In regards to losing PUHI, we expect parents who are high school dropouts to be affected more by the 2005 PUHI contraction than adults with more education. While it is statistically insignificant, the coefficient supports this expectation in magnitude and sign as it is larger in absolute terms than the coefficient for high school graduates or less in Table 2.5, column 1. For high school dropouts: employment, all values associated with hours of employment except working 20-35 hours/week, and employed with ESHI also decrease. While the decrease in employment is puzzling and possibly inconsistent with earlier findings, it is also statistically insignificant and thus we cannot reject that the coefficient equals zero. Further, when we use the ACS data (discussed in two paragraphs) the main results are supported. However, the high negative value of employment might not be inconsistent. Recall from the introduction and model section that people who lose PUHI might choose to work less to re-qualify for PUHI, or might have health problems once losing PUHI that causes them to miss work. The coefficients in panel A suggest that one or both of these situations occurred to those less educated adults.

Analyzing panel B, we expect adults with education levels of college or more to be in higher wage paying jobs and, therefore, not on PUHI. We expect adults in this group to be minimally affected by the 2005 contraction. Looking at the results displayed in panel B, we see all the coefficients are insignificant, economically and statistically, supporting our expectations. Panels A and B of Table 2.9 reveal heterogeneous effects from the contraction once conditioning on education.

Table 2.10 follows the same format as Table 2.9 except that it uses the ACS data instead of the CPS data. Expectations are the same as before—we expect high school dropouts to be affected but adults with more than a high school diploma to be minimally affected, if affected at all. Panel A's results stand in stark contrast to Table 2.9 panel A's employment results and line up better with the main results. Using the less noisy ACS data set, we now find that, for the parents in Missouri who are high school dropouts, the coefficients for employed and employed and working < 20 hours/week are positive and statistically significant.[66] Further, it appears this group seeks employment along the extensive margin as extensive plus intensive weeks worked is positive and significant while the intensive weeks worked is insignificant. These results match up with the main results – high school dropouts seek out employment and seem to seek it out in part time jobs and along the extensive margin. Turning to panel B of Table 2.10, adults with more than a high school diploma seem not to be affected at all. All coefficients, both economically and statistically, are insignificant. The results in Tables 2.9 and 2.10 match up almost exactly as we expect, provide robustness to the main results presented in Tables 2.5 and 2.6, and display the heterogeneous effects of the contraction on different education levels of people.

6.3. Robustness Check Using Different Income Levels

The results presented in Tables 2.11 and 2.12 strongly support the main findings of this paper. These two tables do not condition on education but instead condition on income. The tables follow a similar format to prior tables. Table 2.11 displays results using the CPS data while Table 2.12 displays results using the ACS data. In both tables, panel A depicts results using all adults in the data set between the ages of 19 and 64 and not in the armed forces. The results in panel A are not conditioned on education or income level. Panel B displays results after removing all adults who make more than 4x the FPL. Panel C displays results after removing all adults who make more than 3x the FPL. Panel D displays results after removing all adults who make more than 2x the FPL.

---

[66] In Missouri, there are 6,719 parents who are high school dropouts in the ACS data set during the years 2006 and 2007. In the CPS, there are only 311.

As we move from panel A to panel D we are moving from wealthier to poorer adults; therefore, we expect the results to becoming increasingly greater in absolute magnitude and statistical significance since the contraction affected a very poor group of adults.

In Table 2.11, the coefficients of the three main variables in the CPS data follow the expected trend. As we move from panel A to panel D: PUHI, employed, and employed with ESHI all increase in absolute value (and in the expected direction) as we narrow in on income levels. Further, all three variables become more statistically significant as we narrow in on income (though the coefficient on employed is never statistically significant). Table 2.12, displaying results using the ACS data, also follows expected trends. As we narrow in on a poorer group of adults, employed and employed and working $<$ 20 hours/week increase in magnitude. In all four panels, statistical significance of these two variables is between the 1% and 5% levels. The coefficients associated with employed and working $\geq$ 20 hours/week increase in magnitude but, like the main results, are basically statistically insignificant. In general, the coefficient associated with the extensive plus intensive weeks worked also increases in magnitude but statistical significance is not consistent.

The results presented in Tables 2.11 and 2.12 follow common intuition that as we concentrate more on the group that should be affected it appears they are more affected. The results displayed in Table 2.11 and 2.12 support the main results presented in section 5. One important caveat to this set of results is that as the data is conditioned on income to narrow in on a group of people I could be biasing my results since a selection problem might arise. Conditioning on income is arguably conditioning on an outcome. In other words, I might have reverse causality between income and the dependent variable (my main analysis that conditions by education level clearly avoids this reverse causality problem).

In order to address the above concern, I present results in Table 2.13 that use equation (1) with the dependent variable being a range of incomes, listed at the top of each column. Panel A presents results using the CPS data and panel B presents results using the ACS data. In both panels, there does not appear to be any consistent pattern in the results as no income levels appear to be significantly affected by the 2005 contraction in both data sets other than the income level including parents making 300% to 400% of the FPL. Within this income group, the ACS coefficient is economically insignificant and only statistically significant at the 10% level (table 2.13, panel B, column 4). The CPS data set shows there to be an increase amongst the percentage of parents making less than the FPL, but this is not supported by the larger ACS data set. Additionally, the ACS data set shows there to be an increase in the percentage of parents making 100% to 200% of the FPL. This increase lines up with the results presented in this paper since it appears people are working more in part time jobs; therefore, we should expect their incomes to increase. Moving from 20% to 75% of the FPL to 100% to 200% of the FPL seems like a realistic increase in their income. The coefficient is supported in magnitude by the results using the CPS data set but is not statistically significant. Overall, the values of the coefficients in this table support the idea that the income distribution in Missouri does not seem to be changing due to the 2005 contraction.

6.4. Additional Crowd-out Estimates

Table 2.14 provides additional crowd-out estimates by calculating them for every robustness check performed in this section. The format of the table follows the same format as Table 2.7 except that it has multiple panels. Each panel displays results using one of the robustness checks previously discussed in this section. Since all of the crowd-out estimates displayed are insignificant, it cannot be rejected that the crowd-out resulting from the contraction is 0. The statistical insignificance of all the estimates greatly supports the main findings' statistical insignificance discussed in the previous section. The crowd-out values estimated on employment with ESHI from PUHI range from 0% to 58% and the "crowd-in" estimates range from 0% to 163%. The crowd-out estimates line up with GGN's estimates and the values surveyed by Gruber and Simon (2008), who find a range of 0% to 59%, depending on the group studied. This similarity provides more support to my main findings and to others who study people earning below the poverty level. The crowd-in estimates do not line up with any of the papers reviewed.

The results in panel A, using only the states that border Missouri, strongly support my main estimates as their magnitude, sign, and significance are very similar. The results in panel B show that as adults who are high school dropouts lose PUHI they also lose ESHI. This does not line up with expectations unless these people are in fact trying to earn less money to re-qualify for PUHI or have health problems occurring once they lose their PUHI that prevent them from working (which might very well be the case). Panels C and E also suggest a crowd-in estimate while panels D, F and G suggest a crowd-out estimate. Due to the consistent statistical insignificance of employed with ESHI and crowd-out displayed throughout this table, no real causal crowd-out conclusions can be made.

6.5. State Falsification Tests

State falsification tests are performed as an alternative approach to statistical inference. Figure 2.6 displays results after performing state falsification tests using the CPS data. For these tests, I treat each of the 45 states used as controls as the treated state and run regression equation (1) using the other 44 states and Missouri as the controls, resulting in 45 additional regressions for each dependent variable with a different treated state each time.[67] Each panel in Figure 2.6 displays the respective state's resulting coefficient of the triple interaction term in equation (1) for the respective dependent variable, as labeled on the vertical axis. The horizontal axis simply depicts the number in the data corresponding to a state. The state postal code identifier is labeled for each state next to its corresponding data point. The orange-dashed line is placed at the value corresponding to Missouri's coefficient's value for the respective dependent variable. Only panel E is different in that it depicts two dependent variables on the graph and thus has an extra dashed line corresponding to Missouri's coefficient's value of the second

[67] I also performed the state falsification tests excluding Missouri as one of the controls. Results are almost identical and are available upon request. Further discussion is at the end of this section.

dependent variable. In panel E, the share having public health insurance is on the horizontal axis and the share employed with ESHI is on the vertical axis.

Panel A establishes a credible first stage. No other state has a coefficient that is more negative than Missouri's coefficient. Panel B shows that many states have greater changes in employment during the 2 years following the contraction than Missouri. This is not surprising though as the CPS value for this coefficient was insignificant (reference Table 2.5, column 2). Panel C shows that only two states have a greater change than Missouri for employed parents working 20-35 hours/week. Panel D shows that only four states have a greater change than Missouri for employed parents with ESHI. Oklahoma is one of the four states with a greater increase in ESHI during this timeframe. It is very possible that this is due to the fact that, in November of 2005, Oklahoma started offering subsidies to employers who provided health insurance to employees, and in March of 2007 they began offering subsidies for the self-employed and other individuals (Oklahoma Health Care Authority, 2015).[68]

The main two variables of interest using the CPS data are the share having public health insurance and the share employed with ESHI. Both of these state falsification tests support the results seen in Missouri as being an isolated event that only happened in Missouri. Panel E displays just how different the combined results are for Missouri compared to the rest of the states. Oklahoma is the only other state with as negative a change in PUHI as Missouri and also as positive a change in employed with ESHI.

[68] This offers a possible avenue for future research.

Given the information explained above concerning Oklahoma, this value is actually not surprising and does not cast doubt on the effects seen in Missouri. Figure 2.6 strongly supports the effects shown in this paper resulting from the Medicaid contraction in Missouri. No other state, except Oklahoma, experienced similar effects in the two years following the contraction.

Figure 2.7 displays results after performing state falsification tests using the ACS data and follows the same format as Figure 2.6. Panel A shows that only one other state had a larger increase in employment than Missouri following the contraction.[69] Panel B shows that only one other state had a larger increase in employed and working < 20 hours/week. Panel C shows that seven other states had a greater increase in their intensive plus extensive weeks worked. While problematic, this result does not take away from the belief that people are gaining employment and gaining it in part time jobs following the 2005 contraction. Figure 2.7 only casts doubt if the change in weeks worked in Missouri is along the extensive margin, as concluded earlier. Panel D combines employment and employed and working < 20 hours/week on one graph to display how different the results in Missouri are from the other states. No other state has as great an increase in employment and in employed and working < 20 hours/week as Missouri. Overall, the state falsification tests studied in this subsection support the main conclusions made in this paper--parents in Missouri lost PUHI and reacted by seeking out

[69] Studying what was going on in Rhode Island following 2005 might prove fruitful. Discussion follows in the next paragraph.

employment, mainly in part time jobs. Further, some of these parents likely sought out employment offering ESHI.

Figure 2.7 depicts that the percentage point increase of employment in Rhode Island is clearly much greater than the other 45 states. While the reason for such a disparity is not the focus of this paper, one possible explanation might be in the industry makeup of Rhode Island. In 2005, the top 3 industries contributing to the Gross Domestic Product of Rhode Island were: real estate, rental, and leasing which accounted for 14.4%; finance and insurance which accounted for 11.9%; and manufacturing which accounted for 10.1% of the state's GDP (Wong et al. 2008). The U.S. averages for these three categories in 2005 were 14.5%, 8.8%, and 13.9%, respectively. The difference in percentages between the finance and insurance industries may explain the apparent Rhode Island boom.

2006 and 2007 were the last 2 years before the housing bubble burst. During this same timeframe, the finance and insurance industries were in expansionary periods. Having more of the state depend on finance and insurance than does the U.S. on average, helps explain some of the apparent expansionary time in Rhode Island during the years 2006 and 2007. This also helps explain why Rhode Island experienced a more severe recession than any other New England state and experienced the worst ranked employment growth in the years 2008 and 2009 (Burke, 2014). The finance sector alone accounts for almost 40% of the increased unemployment numbers in Rhode Island compared to the second worst affected New England state – Connecticut (Burke, 2014).

As mentioned in a prior footnote, these state falsification tests were also done excluding Missouri from the set of controls. The only change to Figure 2.6 (which uses the CPS data) when eliminating Missouri as a control is that New York now has a greater positive value for employed with ESHI (0.0375 vs. 0.0371 for Missouri) and thus is just above the orange line in Figure 2.6, panels D and E, instead of just below it. No states change their position relative to Missouri in Figure 2.7 when using the ACS data and excluding Missouri from the controls.

7. Conclusion

Understanding the effects from PUHI contractions and expansions is extremely important. The estimates provided in this paper add to the health insurance employment literature. As the group affected by Missouri's contraction is a subset of the group that the Affordable Care Act will increase the Medicaid limit for (those making ≤ 133% of the FPL), this study provides important reactions which might soon be seen due to the Affordable Care Act.

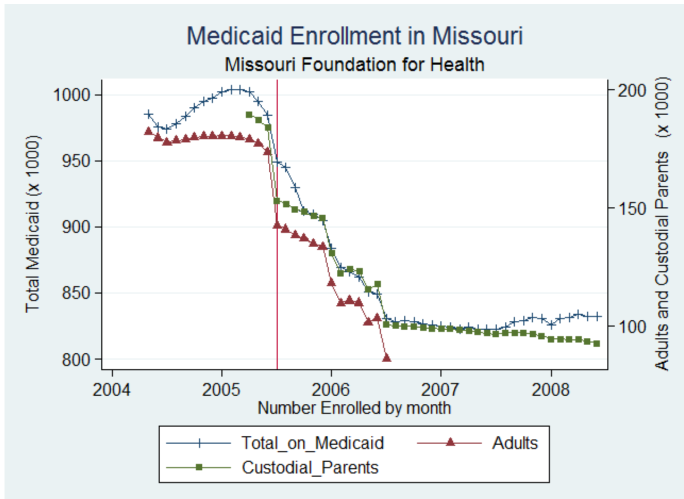
The contraction of public health insurance in Missouri affected many people. The CPS data reveals an economically and statistically significant 5.37 percentage point drop in PUHI amongst parents in Missouri with a high school diploma or less. The PUHI contraction also greatly affected employment. Using the ACS data set, I estimate a statistically significant employment increase of 2.3 percentage points the two years following the contraction amongst this same group of parents. While the coefficient of employment using the CPS data set is insignificant, it is similar in size and sign to the significant one when using the ACS data set. Robustness checks and falsification tests greatly support this employment increase amongst this group of parents.

Results using the two data sets are mixed on whether employment is occurring in part time or full time jobs; therefore, the results cast doubt on whether these people losing PUHI are taking on employment with ESHI. The CPS data set reveals an economically significant, though statistically insignificant shift amongst parents in Missouri with a high school education or less into jobs with ESHI. This suggests that the majority of these parents are gaining employment in full time jobs. The ACS data set reveals that most of the jobs being gained are in part time ones and that they are along the extensive margin. While part time jobs may include ESHI, it is less common than for full time jobs to include it. As most people are changing along the extensive margin, it seems more plausible that they would transition from no work to part time work than to full time work.

In light of the Affordable Care Act, these results are important for policy makers to understand. If these contraction estimates apply in opposite sign to expansion estimates, then we should expect to see individuals quit their jobs due to the Affordable Care Act. Further, the ACS data shows that the individuals quitting their jobs would likely be those who had part time employment. In this situation, individuals would be removing themselves from the employment statistics since they would remove themselves from the labor force, which would tend to increase the unemployment percentage released by the Bureau of Labor Statistics since they were employed and are no longer in the labor force.[70] This might make people think the Affordable Care Act had a negative impact on unemployment, when it really just encouraged people to leave their jobs and vacate the labor force.

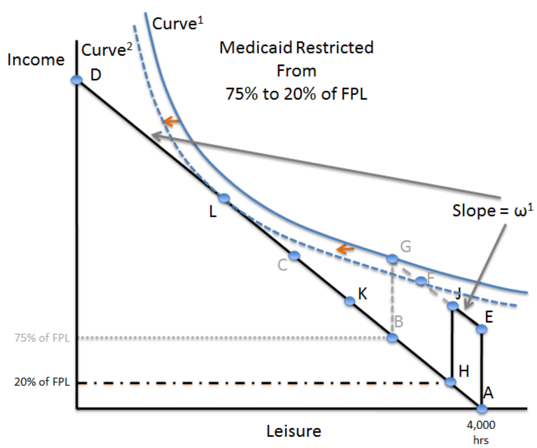
[70] As is well known, the unemployment rate is calculated as the number of people unemployed divided by the number of people in the labor force. The number of people in the labor force equals the number of people employed plus the number of people unemployed. Therefore, anyone who leaves the labor force does not count in these values. Since employed people would leave the labor force, the unemployment percentage would increase.

Figure 2.1: Medicaid Enrollment in Missouri



Notes: The figure above presents aggregate enrollment in Medicaid for the entire population of Missouri and for adults, who were reclassified in April 2005 as custodial parents. Data for this figure comes from The Missouri Foundation of Health.

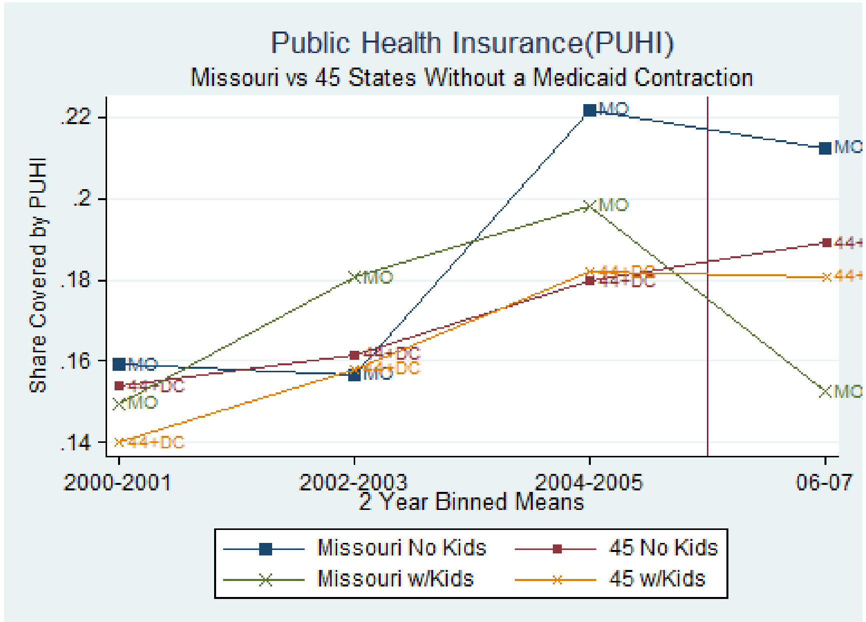
Figure 2.2: Model for Medicaid Contraction



Location Before Contraction	Location After Contraction
E	E
J	J
F	J or somewhere on line KD
G	
C	C
L	L
D	D

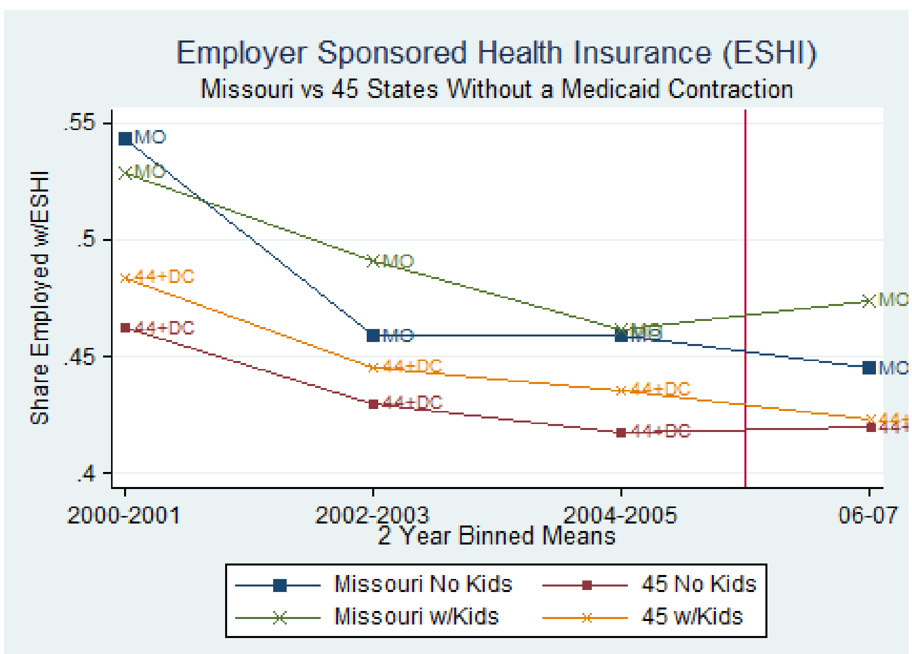
Notes: The figure above and on the left depicts the tradeoff between leisure and income for a household with two adults capable of working. It presents the Medicaid notch that occurs after changing from 75% to 20% of the federal poverty level. The grey, dotted or dashed lines represent the notch when at 75%. The black, solid or dashed lines represent the notch when reduced to 20%. The table on the right depicts possible locations of a household before and after the contraction. The left column gives a possible location of a household prior to the contraction. The right column gives where that household might move to afterwards, given they started in the corresponding row's point before the contraction.

Figure 2.3: Public Health Insurance



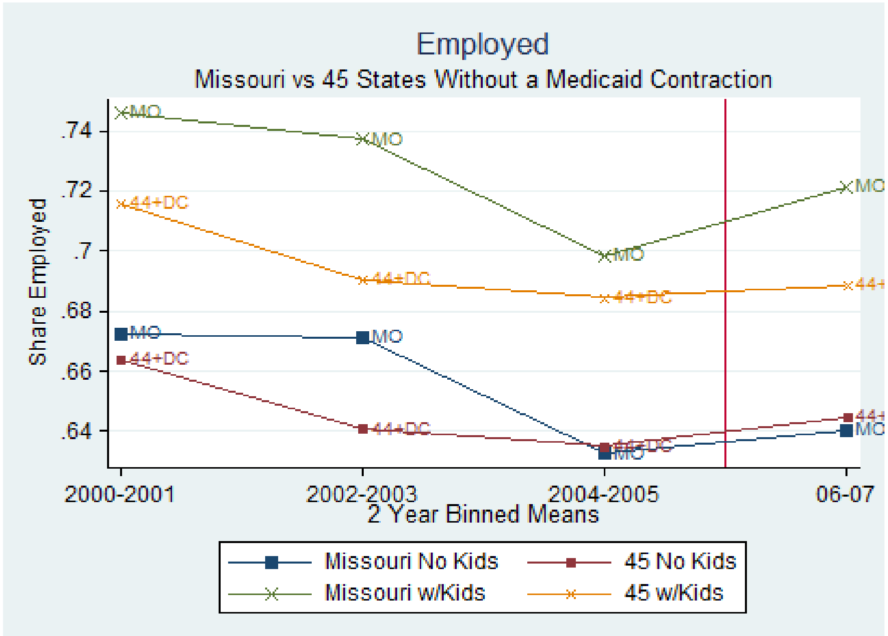
Notes: The figure above represents the share of CPS March respondents ages 19-64, not in the armed forces, and with no more than a high school diploma who report being covered by public health insurance. The figure presents means by 2-year cells, using the appropriate CPS provided weights. The line labeled 44+DC represents DC and the 44 states that did not have a contraction at the same time as Missouri and is labeled 45 in the legend.

Figure 2.4: Employer Sponsored Health Insurance



Notes: The figure above represents the share of CPS March respondents who report having employer sponsored health insurance. See Figure 2.3's notes for more details.

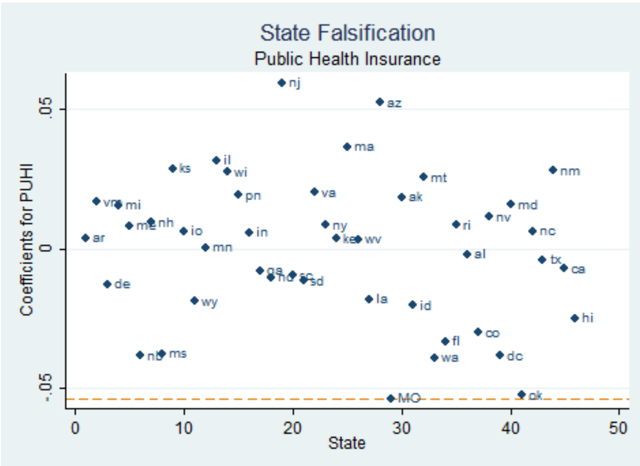
Figure 2.5: Employed



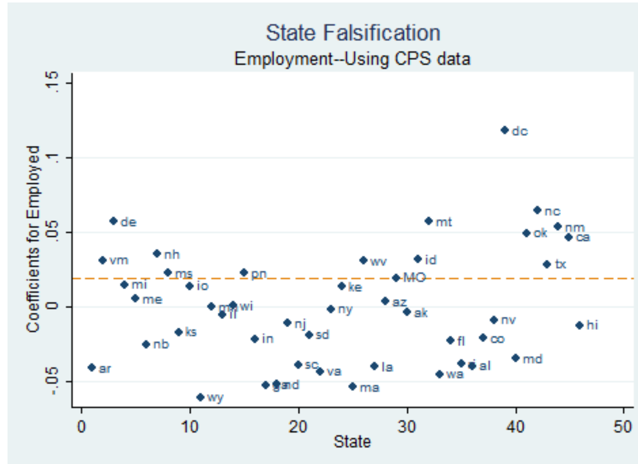
Notes: The figure above represents the share of CPS March respondents who report being employed. See Figure 2.3's notes for more details.

Figure 2.6: CPS State Falsifications

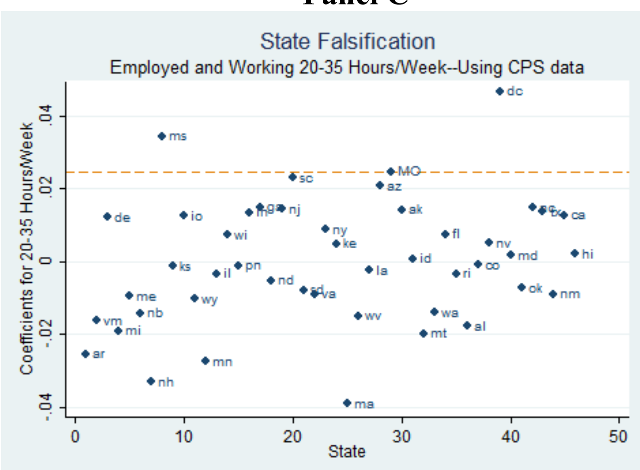
Panel A



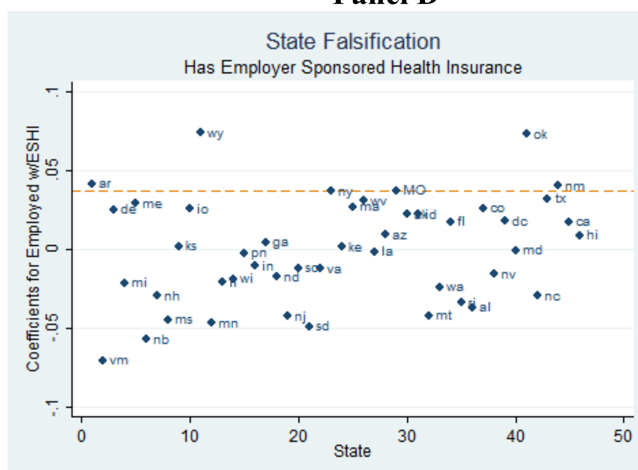
Panel B



Panel C



Panel D



Panel E

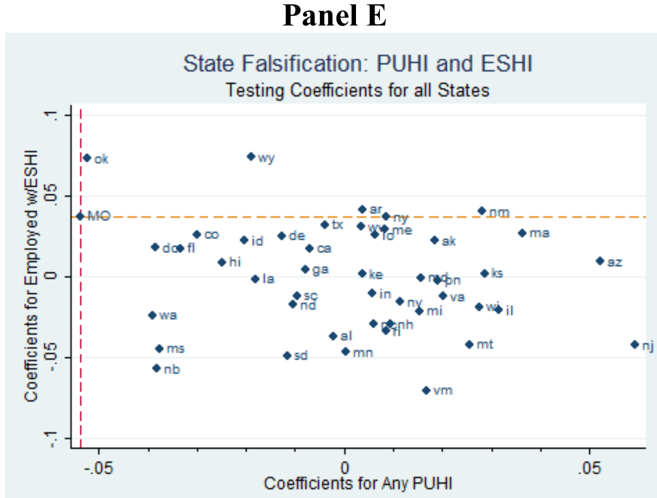
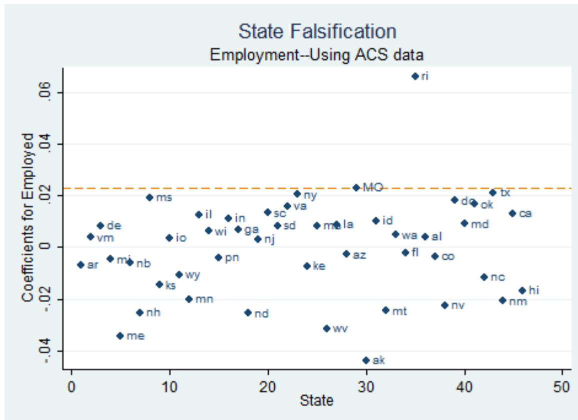


Figure 2.6 continued

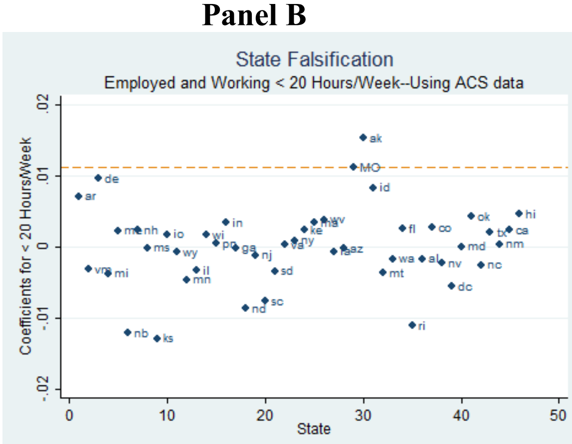
Notes: Figure 2.6 presents the coefficients of interest when running equation (1) and treating each of the 45 states used as controls as the treated one (e.g. Arkansas is used as the treated state while the other 44 states and Missouri are used as the controls). Panels A, B, C, and D display each state's β value for having any PUHI, being employed, being employed and working 20-35 hours/week, and being employed with ESHI, respectively. In these 4 panels, the horizontal axis identifies the state and the vertical axis identifies the dependent variable of interest. Panel E displays Any PUHI on the horizontal axis and employed with ESHI on the vertical axis. The orange (and red for panel E) dashed line designates the value of the coefficient when using Missouri as the treated state.

Figure 2.7: ACS State Falsifications

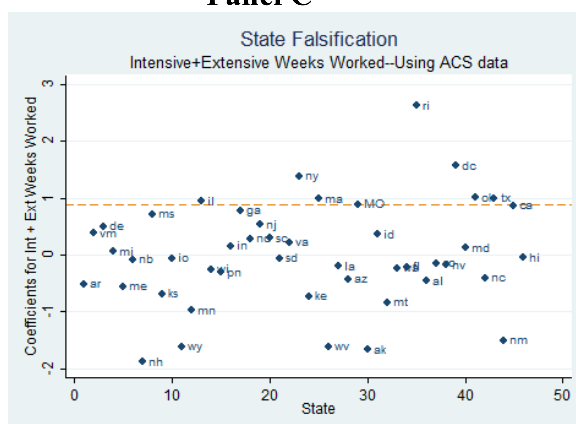
Panel A



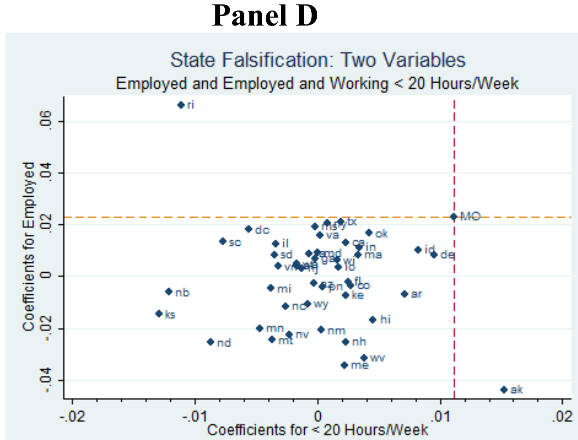
Panel B



Panel C



Panel D



Notes: The figure above follows the same format as Figure 2.6 but uses the ACS data instead of the CPS data. Please see Figure 2.6's notes for more details.

Table 2.1: Missouri's Medicaid Income Changes

Covered Populations	Income Guidelines Prior to Changes in 2005	Current Income Guidelines
Children (up to age 19)	<300% FPL	<300% FPL
Pregnant Women	<185% FPL	<185% FPL
Blind Individuals	<100% FPL	<100% FPL
Parents	< 75% FPL	≤20% FPL

Notes: The table above shows the changes to income limits to qualify for Medicaid when Missouri contracted their Medicaid program. The first column depicts the covered population, the second column depicts the income guidelines prior to 2005, and the third column depicts the income guidelines after the change in 2005.

Table 2.2: 2005 Federal Poverty Levels

Federal Poverty Level in 2005						
Number of People in Household	**20%**	**75%**	**100%**	**200%**	**300%**	**400%**
1	$1,914	$7,178	$9,570	$19,140	$28,710	$38,280
2	$2,566	$9,623	$12,830	$25,660	$38,490	$51,320
3	$3,218	$12,068	$16,090	$32,180	$48,270	$64,360
4	$3,870	$14,513	$19,350	$38,700	$58,050	$77,400
For each additional person add:	$680	$2,550	$3,400	$6,800	$10,200	$13,600

Notes: The table above depicts the federal poverty levels in 2005. These levels are for the lower 48 states and DC. Alaska and Hawaii are higher. The first column gives the number of people in the household. The next six columns depict the dollar amount of the federal poverty level corresponding to the income percentages labeled in the top of the column.

Table 2.3: Summary Statistics Using CPS Data

	Full Sample			Adults with High School Diploma or Less		
	Missouri	45	Diff	Missouri	45	Diff
Any Public Health Insurance	11.57%	11.33%	0.23%	17.98%	16.07%	1.91%
Any Private Health Insurance	69.75%	66.18%	3.57%	58.97%	52.94%	6.03%
Employed	75.10%	71.83%	3.27%	68.80%	65.59%	3.20%
Working < 20 hours per week	4.32%	4.39%	0.08%	3.29%	3.54%	0.25%
Working 20-35 hours per week	11.19%	10.56%	0.63%	10.32%	10.00%	0.32%
Working >= 35 hours per week	59.59%	56.87%	2.72%	55.19%	52.05%	3.14%
Child in HH (age <19)	46.42%	47.47%	1.04%	47.56%	49.92%	2.35%
Age between 40 and 64	52.07%	52.05%	0.02%	54.28%	52.41%	1.88%
High School Dropout	9.11%	13.14%	4.02%	20.81%	29.82%	9.01%
High School Graduate	34.68%	30.92%	3.76%	79.19%	70.18%	9.01%
Some College or College Graduate	48.12%	47.33%	0.79%	0.00%	0.00%	0.00%
White	86.42%	80.64%	5.78%	85.05%	79.45%	5.60%
Black	10.62%	12.61%	1.99%	12.62%	15.13%	2.51%
Other	2.96%	6.75%	3.79%	2.32%	5.42%	3.10%
% on Official_Poverty (Off. Pov.)	9.27%	10.51%	1.24%	13.86%	16.07%	2.21%
% Unemployed	3.97%	3.92%	0.05%	5.68%	5.25%	0.43%
% between 20%-75% of Off. Pov.	4.29%	4.64%	0.35%	6.71%	7.29%	0.58%

Notes: This table reports summary statistics using the CPS data after using the person-level sample weights (health weights are used for health insurance variables). The sample is restricted to the years 2000 to 2007, adults ages 19-64, and adults not in the armed forces. 45 includes DC and all states except those that had a contraction at the same time as Missouri (Tennessee, Oregon, Utah, Ohio, and Connecticut are omitted). The first 3 columns depict averages using all the adults in the CPS. The final three columns depict averages using only adults with a high school diploma or less (the data that is used for the main results of this paper). The columns labeled "Diff" gives the absolute value of the difference between Missouri's percentage and the corresponding controls' percentage.

Table 2.4: Summary Statistics Using ACS Data

	Full Sample			Adults with High School Diploma or Less		
	Missouri	45	Diff	Missouri	45	Diff
Any Public Health Insurance	The ACS data does not have this information during the time periods of interest.					
Any Private Health Insurance						
Employed	74.43%	73.04%	1.39%	68.09%	66.65%	1.44%
Working < 20 hours per week	2.99%	2.90%	0.09%	2.49%	2.46%	0.03%
Working 20-35 hours per week	9.00%	8.76%	0.24%	8.41%	8.14%	0.27%
Working >= 35 hours per week	62.43%	61.36%	1.07%	57.19%	56.04%	1.15%
Child in HH (age <19)	45.57%	46.84%	1.28%	45.94%	49.51%	3.57%
Age between 40 and 64	53.69%	52.62%	1.07%	55.43%	52.69%	2.73%
High School Dropout	9.94%	11.75%	1.81%	19.49%	24.02%	4.53%
High School Graduate	41.07%	37.18%	3.89%	80.51%	75.98%	4.53%
Some College or College Graduate	48.99%	51.07%	2.08%	0.00%	0.00%	0.00%
White	85.36%	74.84%	10.52%	83.98%	71.26%	12.72%
Black	10.56%	12.02%	1.45%	11.98%	14.17%	2.19%
Other	4.08%	13.14%	9.07%	4.04%	14.57%	10.53%
% on Official_Poverty (Off. Pov.)	11.11%	11.22%	0.10%	14.85%	15.72%	0.87%
% Unemployed	4.26%	4.47%	0.22%	5.62%	5.72%	0.10%
% between 20%-75% of Off. Pov.	2.87%	2.90%	0.03%	4.37%	4.66%	0.29%

Notes: This table reports summary statistics using the ACS data after using the person-level sample weights. The table follows Table 2.3's same format. See Table 2.3's notes for more details.

Table 2.5: CPS DDD Results – Adults with a High School Diploma or Less

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ESHI = Employer Sponsored Private Health Insurance	Has Public Health Insurance	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Employed and working 20-35 hrs/week	Employed and working ≥ 35 hrs/week	Employed with ESHI
MO x Post 2005 x Kid	-0.0537**	0.0190	0.0054	0.0136	0.0247	-0.0111	0.0371
2-Stage Block Bootstrapped Std Errors	(0.0221)	(0.0249)	(0.0099)	(0.0247)	(0.0162)	(0.0271)	(0.0282)
R^2	0.9351	0.9168	0.751775	0.8973334	0.8039	0.8635368	0.9336161
Mean of Dependent Variable	0.1684	0.6709	0.03967	0.6312534	0.1059	0.5253764	0.4405983

** p<0.05

Notes: The sample uses CPS data and includes Missouri and the 45 states between 2000 and 2007 using the health insurance weights for the health insurance variables and person-level sample weights for the employment variables. Each column depicts results running the difference-in-difference-in-difference equation with the dependent variable as shown in the top row. The individual level data is collapsed to the state-by-year-by-child status aggregate level to run the regressions after eliminating everyone with better than a high school diploma. The sample consists of means for each state, year, and whether the respondents had children or not (resulting in 736 observations: 46 states over 8 years with children or not). State fixed effects, year fixed effects, a dummy variable = 1 if the group has children, and all possible pairwise interactions between these three effects are included but not shown. Standard errors are calculated using the two-stage block bootstrap method described in the text. This method is repeated 800 times with replacement.

Table 2.6: ACS DDD Results – Adults with a High School Diploma or Less

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Employed and working 20-35 hrs/week	Employed and working ≥ 35 hrs/week	Intensive Weeks Worked	Extensive+ Intensive Weeks Worked
MO x Post 2005 x Kid	0.0231**	0.0111***	0.0121	0.0024	0.0097	-0.0577	0.89**
2-Stage Block Bootstrapped Std Errors	(0.0091)	(0.0026)	(0.0090)	(0.0051)	(0.0088)	(0.2905)	(0.4104)
R^2	0.9732	0.8073	0.9699	0.8767	0.9590	0.9356	0.9774
Mean of Dependent Variable	0.6811	0.0258	0.6552	0.0833	0.5719	44.6274	35.1749

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table differs from Table 2.4 in that it uses ACS data as opposed to CPS data. Column (6) depicts the change in weeks worked conditional on working. Column (7) depicts the change in weeks worked unconditionally. Other than these differences, Table 2.6 follows the same format as Table 2.5. Please refer to Table 2.5's notes for more details.

Table 2.7: Crowd-out Estimate

	(1)	(2)	(3)	(4)
ESHI = Employer Sponsored Private Health Insurance	Has Public Health Insurance	Employed	Employed with ESHI	Crowdout = Δ ESHI / Δ Public
MO x Post 2005 x Kid	-0.0537**	0.0231**	0.0371	-0.6898
2-Stage Block Bootstrapped Std Errors	(0.0221)	(0.0091)	(0.0282)	(6.9323)
R^2	0.9351	0.9732	0.9336	
Mean of Dependent Variable	0.1684	0.6811	0.4406	

** p<0.05

Notes: This table presents crowd-out estimates using the CPS data for both health insurance estimates and the ACS data for the employment estimate as detailed in Tables 2.5 and 2.6. Columns 1, 2, and 3 are pulled from the appropriate columns in Tables 2.5 and 2.6. The crowd-out estimate from PUHI on employed with ESHI is presented in column 4. Two-stage block bootstrapped standard errors are reported.

Table 2.8: CPS and ACS Regressions Results Using Border States

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: CPS DDD Regression Results								
ESHI = Employer Sponsored Private Health Insurance	Has Public Health Insurance	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Employed and working 20-35 hrs/week	Employed and working ≥ 35 hrs/week	Employed with ESHI	
MO x Post 2005 x Kid	-.0512*	0.0228	0.0062	0.0166	0.0266	-0.0100	0.0297	
2-Stage Block Bootstrapped Std Errors	(0.0274)	(0.0288)	(0.0122)	(0.0305)	(0.0187)	(0.0292)	(0.0330)	
R^2	0.8812	0.9367	0.8035	0.8997	0.7257	0.8372	0.9174	
Mean of Dependent Variable	0.1560	0.6806	0.0397	0.6409	0.1026	0.5383	0.4626	
Panel B: ACS DDD Regression Results								
	Health insurance information is not available in the ACS during the studied time interval	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Employed and working 20-35 hrs/week	Employed and working ≥ 35 hrs/week	Intensive Weeks Worked	Extensive + Intensive Weeks Worked
MO x Post 2005 x Kid		0.0214*	0.0121**	0.0095	0.0013	0.0082	0.1142	0.8654*
2-Stage Block Bootstrapped Std Errors		(0.0099)	(0.0039)	(0.0101)	(0.0061)	(0.0103)	(0.3350)	(0.4613)
R^2		0.9784	0.7560	0.9779	0.8671	0.9671	0.9254	0.9807
Mean of Dependent Variable		0.6865	0.0252	0.6612	0.0794	0.5818	44.83	35.6

** p<0.05, * p<0.1

Notes: The table above uses the states that border Missouri (minus Tennessee since they had a major contraction at the same time and plus Indiana since they are very close but not actually touching Missouri). Panel A depicts results using the CPS data while panel B uses ACS data. See Table 2.5 for panel A details and Table 2.6 for panel B details. The number of observations decreases to 144 due to only using 9 states in the regression. Both panels use the DDD specification discussed in the paper. Each column depicts results running the DDD equation with the dependent variable as shown in the top row. State fixed effects, year fixed effects, a dummy variable = 1 if the group has children, and all possible pairwise interactions between these three effects are included but not shown. Standard errors are calculated using the two-stage block bootstrap method described in the text. The two-stage block bootstrap is repeated 800 times with replacement.

Table 2.9: Robustness Check Using CPS Data: Different Education Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: CPS DDD Regression Results: Adults Who Are High School Dropouts							
ESHI = Employer Sponsored Private Health Insurance	Has Public Health Insurance	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Employed and working 20-35 hrs/week	Employed and working ≥ 35 hrs/week	Employed with ESHI
MO x Post 2005 x Kid	-0.0652	-0.0460	-0.0119	-0.0341	0.0173	-0.0515	-0.0168
2-Stage Block Bootstrapped Std Errors	0.0561	0.0597	0.0202	0.0620	0.0324	0.0575	0.0544
R^2	0.8693	0.8060	0.6102	0.7894	0.6322	0.7730	0.7720
Mean of Dependent Variable	0.2544	0.5435	0.0387	0.5047	0.0977	0.4070	0.2627
Panel B: CPS DDD Regression Results: Adults with More Than a High School Diploma							
MO x Post 2005 x Kid	-0.0148	-0.0076	0.0009	-0.0084	-0.0200	0.0116	-0.0240
2-Stage Block Bootstrapped Std Errors	(0.0131)	(0.0189)	(0.0095)	(0.0195)	(0.0153)	(0.0218)	(0.0231)
R^2	0.8875	0.8709	0.7715	0.8355	0.8306	0.8333	0.9203
Mean of Dependent Variable	0.0851	0.7789	0.0542	0.7247	0.1158	0.6088	0.6392

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table above uses CPS data on the 45 states used as controls and Missouri. Panel A depicts results using adults who did not graduate from high school. Panel B depicts results using adults with some college or more. Standard errors are calculated using the two-stage block bootstrap method described in the text. The two-stage block bootstrap is repeated 800 times with replacement. Other than the two panels, the format is the same as Table 2.5. Please see Table 2.5's notes for more details.

Table 2.10: Robustness Check Using ACS Data: Different Education Levels

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: ACS DDD Regression Results: Adults Who Are High School Dropouts							
	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Employed and working 20-35 hrs/week	Employed and working ≥ 35 hrs/week	Intensive Weeks Worked	Extensive+ Intensive Weeks Worked
MO x Post 2005 x Kid	0.0382*	0.0241***	0.0144	-0.0028	0.0173	1.2013	2.2345**
2-Stage Block Bootstrapped Std Errors	(0.0204)	(0.0067)	(0.0223)	(0.0108)	(0.0202)	(0.7831)	(0.9535)
R^2	0.8821	0.6897	0.8776	0.7177	0.8769	0.8220	0.8981
Mean of Dependent Variable	0.0699	1.0273	0.0276	-0.0388	0.0383	0.0286	0.0792
Panel B: ACS DDD Regression Results: Adults with More Than a High School Diploma							
MO x Post 2005 x Kid	0.0087	-0.0002	0.0089	0.0032	0.0057	-0.1096	0.5342
2-Stage Block Bootstrapped Std Errors	(0.0063)	(0.0030)	(0.0072)	(0.0049)	(0.0082)	(0.2068)	(0.3310)
R^2	0.9406	0.8356	0.9211	0.9177	0.9197	0.8918	0.9445
Mean of Dependent Variable	0.8011	0.0335	0.7675	0.0958	0.6717	46.01	40.68

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table above uses ACS data on the 45 states used as controls and Missouri. Panel A depicts results using adults who did not graduate from high school. Panel B depicts results using adults with some college or more. Standard errors are calculated using the two-stage block bootstrap method described in the text. The two-stage block bootstrap is repeated 800 times with replacement. Other than the two panels, the format is the same as Table 2.6. Please see Table 2.6's notes for details.

Table 2.11: Robustness Check Narrowing In On Income Using the CPS

ESHI = Employer Sponsored Private Health Insurance	(1) Has Public Health Insurance	(2) Employed	(3) Employed with ESHI
Panel A: All Adults No Matter Their Income Level			
MO x Post 2005 x Kid	-0.0335**	0.0074	0.0044
2-Stage Block Bootstrapped Std Errors	(0.0131)	(0.0154)	(0.0177)
R^2	0.9441	0.9497	0.9558
Mean of Dependent Variable	0.1210	0.7309	0.5529
Panel B: Adults Who Make ≤ 4x the Federal Poverty Level			
MO x Post 2005 x Kid	-0.0433**	0.0245	-0.0032
2-Stage Block Bootstrapped Std Errors	(0.0193)	(0.0224)	(0.0241)
R^2	0.9378	0.9563	0.9579
Mean of Dependent Variable	0.1706	0.6575	0.4157
Panel C: Adults Who Make ≤ 3x the Federal Poverty Level			
MO x Post 2005 x Kid	-0.0747***	0.0410	0.014144
2-Stage Block Bootstrapped Std Errors	(0.0243)	(0.0279)	(0.0262)
R^2	0.9317	0.9459	0.9450
Mean of Dependent Variable	0.2064	0.6095	0.3342
Panel D: Adults Who Make ≤ 2x the Federal Poverty Level			
MO x Post 2005 x Kid	-0.1362***	0.0513	0.0532*
2-Stage Block Bootstrapped Std Errors	(0.0349)	(0.0356)	(0.0290)
R^2	0.9199	0.9324	0.9136
Mean of Dependent Variable	0.2718	0.5274	0.2135

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The table above uses CPS data and the 45 states and Missouri from 2000 to 2007. Panel A, B, C, and D depict, respectively, results using all people, and those people making ≤ 4x, ≤ 3x, and ≤ 2x the federal poverty level. Each column depicts results running the DDD equation (1) with the dependent variable as shown in the top row. State fixed effects, year fixed effects, a dummy variable = 1 if the group has children, and all possible pairwise interactions between these three effects are included but not shown. Standard errors are calculated using the two-stage block bootstrap method described in the text. The two-stage block bootstrap is repeated 800 times with replacement.

Table 2.12: Robustness Check Narrowing In On Income Using the ACS

	(1)	(2)	(3)	(4)
	Employed	Employed and working < 20 hrs/week	Employed and working ≥ 20 hrs/week	Extensive + Intensive Weeks Worked
Panel A: All Adults, No Matter Their Income Level				
MO x Post 2005 x Kid	0.0162***	0.0056***	0.0107*	0.7102***
2-Stage Block Bootstrapped Std Errors	(0.0057)	(0.0020)	(0.0059)	(0.0253)
R^2	0.9822	0.8792	0.9774	0.9845
Mean of Dependent Variable	0.7415	0.0296	0.7118	37.9389
Panel B: Adults Who Make ≤ 4x the Federal Poverty Level				
MO x Post 2005 x Kid	0.0192**	0.0079***	0.0114	0.7629*
2-Stage Block Bootstrapped Std Errors	(0.0076)	(0.0028)	(0.0078)	(0.3856)
R^2	0.9806	0.8568	0.9783	0.9836
Mean of Dependent Variable	0.6739	0.0336	0.6401	34.1396
Panel C: Adults Who Make ≤ 3x the Federal Poverty Level				
MO x Post 2005 x Kid	0.022**	0.0112***	0.0110	0.6248
2-Stage Block Bootstrapped Std Errors	(0.0094)	(0.0036)	(0.0095)	(0.4124)
R^2	0.9717	0.8485	0.9711	0.9781
Mean of Dependent Variable	0.6276	0.0366	0.5908	31.4845
Panel D: Adults Who Make ≤ 2x the Federal Poverty Level				
MO x Post 2005 x Kid	0.0355**	0.0146***	0.0210	1.0608*
2-Stage Block Bootstrapped Std Errors	(0.0138)	(0.0049)	(0.0131)	(0.6279)
R^2	0.9585	0.8606	0.9605	0.9698
Mean of Dependent Variable	0.5464	0.0425	0.5037	26.7116

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table above uses ACS data and the 45 states from 2000 to 2007. The format is the same as Table 2.11. See Table 2.11's notes for more details.

Table 2.13: Checking If Missouri Had an Income Distribution Change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: CPS DDD Regression Results, All Adults in Sample							
	Less Than 1x the FPL	(1 to 2) x the FPL	(2 to 3) x the FPL	(3 to 4) x the FPL	(4 to 5) x the FPL	(5 to 6) x the FPL	(6 to 7) x the FPL
MO x Post 2005 x Kid	0.0254**	0.0208	-0.0152	-0.0382***	-0.0160	0.0047	0.0103
2-Stage Block Bootstrapped Std Errors	(0.0107)	(0.0135)	(0.0144)	(0.0132)	(0.0122)	(0.0103)	(0.0079)
R^2	0.9110	0.9303	0.8861	0.7894	0.7202	0.8091	0.8397
Mean of Dependent Variable	0.1030	0.1536	0.1676	0.1511	0.1206	0.0875	0.0618
Panel B: ACS DDD Regression Results, All Adults in Sample							
	Less Than 1x the FPL	(1 to 2) x the FPL	(2 to 3) x the FPL	(3 to 4) x the FPL	(4 to 5) x the FPL	More than 5x the FPL	
MO x Post 2005 x Kid	0.0050	0.0106**	-0.0001	-0.0089*	-0.0057	-0.0009	
2-Stage Block Bootstrapped Std Errors	(0.0045)	(0.0050)	(0.0051)	(0.0046)	(0.0042)	(0.0058)	
R^2	0.9729152	0.9792	0.9635	0.9220	0.8742	0.9944	
Mean of Dependent Variable	0.1124736	0.1554	0.1704	0.1541	0.1194	0.2883	

*** p<0.01, ** p<0.05, * p<0.1

Notes: The table above uses the 45 states as the controls. Panel A depicts results using the CPS data while panel B uses ACS data. Both panels use the same DDD specification that is discussed in the paper but change the dependent variables in order to concentrate on the income levels to see if the income distribution is changing in Missouri. Each column depicts results running DDD equation (1) with the dependent variable as shown in the top row. State fixed effects, year fixed effects, a dummy variable = 1 if the group has children, and the all pairwise interactions between these three effects are included but not shown. Standard errors are calculated using the two-stage block bootstrap method described in the text. The two-stage block bootstrap is repeated 800 times with replacement.

Table 2.14: Additional Crowd-out Estimates

ESHI = Employer Sponsored Private Health Insurance	(1) Has Public Health Insurance	(2) Employed	(3) Employed with ESHI	(4) Crowdout = Δ ESHI / Δ Public
Panel A: Adults in Border States				
MO x Post 2005 x Kid	-.0512*	0.0214*	0.0297	-0.5811
2-Stage Block Bootstrapped Std Errors	(0.0274)	(0.0099)	(0.0330)	(8.6690)
R^2	0.8812	0.9784	0.9174	
Mean of Dependent Variable	0.1560	0.6865	0.4626	
Panel B: Adults Who Are High School Dropouts				
MO x Post 2005 x Kid	-0.0652	0.0241***	-0.0168	0.2569
2-Stage Block Bootstrapped Std Errors	(0.0561)	(0.0067)	(0.0544)	(10.2773)
R^2	0.8693	0.6897	0.7720	
Mean of Dependent Variable	0.2544	1.0273	0.2627	
Panel C: Adults With More Than a High School Diploma				
MO x Post 2005 x Kid	-0.0148	-0.0002	-0.0240	1.6227
2-Stage Block Bootstrapped Std Errors	(0.0131)	(0.0030)	(0.0231)	(31.6668)
R^2	0.8875	0.8356	0.9203	
Mean of Dependent Variable	0.0851	0.0335	0.6392	
Panel D: All Adults, No Matter Their Income				
MO x Post 2005 x Kid	-0.0335**	0.0162***	0.0044	-0.1327
2-Stage Block Bootstrapped Std Errors	(0.0131)	(0.0057)	(0.0177)	(1.3069)
R^2	0.9441	0.9822	0.9558	
Mean of Dependent Variable	0.1210	0.7415	0.5529	
Panel E: All Adults, Who Make ≤ 4x the Federal Poverty Level				
MO x Post 2005 x Kid	-0.0433**	0.0192**	-0.0032	0.0734
2-Stage Block Bootstrapped Std Errors	(0.0193)	(0.0076)	(0.0241)	(2.8299)
R^2	0.9378	0.9806	0.9579	
Mean of Dependent Variable	0.1706	0.6739	0.4157	
Panel F: All Adults, Who Make ≤ 3x the Federal Poverty Level				
MO x Post 2005 x Kid	-0.0747***	0.0410	0.014144	-0.1894
2-Stage Block Bootstrapped Std Errors	(0.0243)	(0.0279)	(0.0262)	(0.5946)
R^2	0.9317	0.9459	0.9450	
Mean of Dependent Variable	0.2064	0.6095	0.3342	
Panel G: All Adults, Who Make ≤ 2x the Federal Poverty Level				
MO x Post 2005 x Kid	-0.1362***	0.0355**	0.0532*	-0.3903
2-Stage Block Bootstrapped Std Errors	(0.0349)	(0.0138)	(0.0290)	(0.2874)
R^2	0.9199	0.9585	0.9136	
Mean of Dependent Variable	0.2718	0.5464	0.2135	

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table presents crowd-out estimates for all the robustness checks in Section 6 of the paper with results displayed in Tables 2.8-2.13. The format is the same as Table 2.7 except that we now have multiple panels. Panel A displays regressions results using the states that border Missouri. Panels B and C display regression results using adults who are high school dropouts and adults with more than a high school diploma, respectively. Panel D displays all adults, no matter their income or education level. Panels E, F, and G display regression results using adults who make ≤ 4x the FPL, ≤ 3x the FPL, and ≤ 2x the FPL, respectively. See Table 2.7's notes for more details. Standard errors are calculated using the two-stage block bootstrap method described in the text. The two-stage block bootstrap is repeated 800 times with replacement.

Chapter 3: Effects of OK Subsidies to Employers Offering Health Insurance

1. Introduction

In this research proposal, I describe plans for a project examining the impacts of subsidies to employer sponsored health insurance plans. Beginning in 2006, the Oklahoma Health Care Authority began offering subsidies to firms offering private health insurance to their employees (firms and employees had to satisfy certain conditions that will be detailed later). Does offering such a subsidy result in an increase in employer sponsored health insurance, improvement in health, and decrease in emergency room visits? If there is an increase in employer sponsored health insurance, is it crowding-out private and/or public health insurance? Finally, since the subsidy effectively decreases the wage firms pay to workers while also increasing the total compensation workers receive, is there a corresponding increase in employment along the extensive (workers entering the market) and/or intensive (workers working more hours) margin? Taking advantage of a sudden change in legislation that resulted in Oklahoma offering subsidies to firms offering health insurance to employees, I am able to estimate the effects on employer sponsored health insurance, health, and emergency room visits; calculate crowd-out estimates that occur on both private and public health insurance; and analyze labor supply effects on both the extensive and intensive margin.

The effects of health care are of great importance to U.S. policy makers due to the implementation of the Affordable Care Act.[71] The Act requires most US citizens and

[71] For more detailed information about the Affordable Care Act, please reference the US Department of Health and Human Services website at http://www.hhs.gov/healthcare/rights/.

legal residents to have health insurance coverage and creates state-based exchanges through which individuals and small businesses can purchase coverage. Among many parts to the Act, firms with 50 or more full-time employees that do not offer health insurance coverage are assessed fees based on the year and their total number of employees. Understanding the effects from the implementation of the Affordable Care Act is crucial to be able to prepare and plan for side-effects that might occur. While Oklahoma's legislative changes do not impose penalties on firms who fail to offer health insurance or on individuals who do not have health insurance, it is similar to the Affordable Care Act in that it creates a financial incentive for firms to purchase health insurance for their employees. Offering subsidies to employers, as is done in Oklahoma, and imposing penalties on employers, as is done in the Affordable Care Act, both encourage firms to offer health insurance and suggests that the effects found in this proposal may also apply to the ones we might see resulting from the Affordable Care Act (though the Act should have a greater effect since it also has an individual mandate that should increase health insurance demand as it incentivizes individuals to obtain health insurance).

In late 2005, Oklahoma implemented legislation that provided subsidies to certain firms for certain employees.[72] The key changes studied in this proposal are that Oklahoma's Department of Health Services began offering subsidies ranging between 65% and 85% of premium health insurance costs to firms with a small number of

[72] All information in this paragraph and in concern with Oklahoma's health insurance changes are found at Oklahoma Health Care Authority's website after examining archived annual reports located at: http://www.okhca.org/research.aspx?id=9662&parts=7447.

employees (ranging between 25 and 99 employees from 2005 to 2009). Employees eligible for the subsidy of health insurance had to be in households making less than certain income thresholds (ranging between 185% and 200% of the FPL from 2005 and 2009). Further, in 2007, the subsidies expanded to include some adults who were self-employed, unemployed, or working disabled and met the income thresholds as specified above. The subsidies and health insurance expansion led to approximately 21,500 adults receiving health insurance by June of 2009. This proposal investigates the questions proposed in the first paragraph of this proposal by comparing the changes of adults in Oklahoma to adults in other states before and after the subsidies began.

Assuming adults value health insurance and insurance companies do not adjust prices due to a subsidy on the service they provide (e.g. they raise their rates because they know the government is now providing a subsidy), we expect a government sponsored subsidy for employer sponsored health insurance (ESHI) to induce adults and businesses to obtain ESHI. If people gain ESHI, health should improve. Health might improve since people are now covered by health insurance and can, therefore, take more preventative actions. However, health might decline because people may take more risks since they now have health insurance coverage (popularly known as moral hazard). In general, we expect the former to outweigh the latter. In this proposal, self-reported health is used as a proxy for health. In addition to having well known measurement problems, self-reported health has the added complication that it might worsen after receiving health care insurance simply because people become more aware of their poor health status. Emergency room visits might increase or decrease for the same reasons that health might improve or degrade. We expect emergency room visits to negatively correlate with health changes as healthier people would need to go to the emergency room less, all else equal. While also serving as a proxy to health, a decrease in emergency room visits might help offset the subsidies given to employers.[73] Since the possible effects are ambiguous, empirical strategies and estimations are necessary to arm policy makers with the proper knowledge for future actions.

We know that any adults who gain ESHI due to this subsidy were, prior to gaining ESHI, in one of three categories: those with no health insurance, those who had some form of public health insurance, or those who had some other type of private insurance not through their employer. Since the adults gaining ESHI come from one of these three categories, we expect to either see no effect or some crowd-out of public and/or other forms of private health insurance resulting from the increase in ESHI and therefore, the subsidy offered by the government. We do not expect to see any crowd-in; that is, an increase in public or some other form of private health insurance resulting from the subsidy on ESHI. As will be shown in the model section, a subsidy from the government to employers offering ESHI effectively decreases the nominal wage the firm is paying for their employees while also increasing the total compensation employees are receiving. Due to total compensation increasing at little to no expense to the firm, we expect firms to employ more labor on the extensive or intensive margin.

[73] While not the focus of this proposal, future research could perform a cost/benefit analysis using the subsidies and change in emergency rooms visits (a decrease would be a benefit while an increase would be an additional cost).

Taking advantage of the across-state variation of the subsidy, I use state-by-year difference-in-difference (DD) analysis to compare adults in Oklahoma to adults in other similar states before and after the subsidy was offered. This methodology allows me to identify the causal effect of the subsidy on: ESHI, self-reported health, emergency room visits, crowd-out of public and other private health insurance coverage, and employment. In preliminary results, I find that following the introduction of the subsidy, adults in Oklahoma experienced a 3.72 percentage point increase in ESHI, experienced a slight decline in self-perceived health status, and used the emergency room more. Further, there was no crowd-out from public health insurance.[74] There was a crowding-out of other forms of private health insurance resulting from ESHI of approximately 4% (though this value is statistically insignificant), and employment effects were negligible.[75] This proposal confirms the robustness of these results by testing different sets of controls and using different lengths of year intervals for the pre and post time periods. More robust and falsification tests are planned and described in the last section.

This proposal proceeds as follows. Section 2 reviews the related literature and details how my proposal adds to and improves on past research. Section 3 gives the relevant background on Oklahoma's health care reform. Section 4 builds a basic labor

[74] The fact that there is no change in public health insurance may suggest that the program did in fact crowd-out public health insurance. Further discussion and explanation is given in the Effects on Health Insurance subsection.

[75] At the same time that ESHI subsidies were offered, many changes were made that increased the number of people enrolled in the state's Medicaid program. The increase in public health insurance due to legislative changes occurring at the same time the subsidies were offered undoubtedly affects the calculated crowd-out estimates and possibly all outcomes. Further research is needed to untangle the two effects and determine the effects resulting from the introduction of the subsidies. Discussion of this topic is continued in the final section.

supply and demand model and shows how the subsidy should theoretically affect employment and total compensation. Section 5 explains the primary data used, details how I narrow in on the observations used in the study, and gives the empirical strategy. Section 6 provides preliminary results. Section 7 provides plans for further implementation.

2. Related Literature

My results build on a large body of literature studying the effects from health insurance programs on the labor market, health, emergency room visits, and the crowd-out on other forms of health insurance. Most of the studies focus on public health insurance programs (e.g. Medicaid) and how expansions or contractions led to certain effects. The results from this body of literature have some common and some mixed results.

The literature on labor market effects from health insurance programs is vast. Gruber (2000) and Gruber and Madrian (2002) provide an overview of the empirical studies on the effects of health insurance on labor supply in the US. They explain that many of the studies they review have problematic identification strategies. The identification problems in the papers they review arise because of the collinearity of Medicaid and Aid to Families with Dependent Children; the independent relationship between health status on welfare and labor supply; the noisy measure of the underlying value of Medicaid to potential recipients resulting in attenuation bias; the probable reverse causality between labor force participation decisions and variation in state Medicaid expenditures; and/or to assuming that a husband's ESHI is exogenous. Ignoring these identification problems, the papers they review generally agree that health insurance has no labor supply effect on low income mothers, but does affect labor force participation and job choice for possible retirees and secondary earners. In contrast to these conclusions, Yelowitz (1995) finds that increasing Medicaid's income limit increases the labor force participation of divorced and separated, but not never-married, women. The identification strategy I use, across-state variation, improves on these earlier papers.

In more recent studies, Decker and Selck (2012) and Strumpf (2011), both using datasets from the 1960's and 1970's, find no impact from Medicaid on the labor force participation of women. Baicker et al. (2013), using OLS and 2SLS, examine the employment effects of Oregon’s public health insurance lottery and find small and statistically insignificant changes in labor market outcomes (employment, earnings, or earnings above the FPL). Azuara and Marinescu (2011), Barros (2008), and Campos-Vazquez and Knox (2013), using a difference-in-difference approach, study the employment effects of Mexico's Seguro Popular program--a national free or subsidized health insurance program. All three find no impact of Seguro Popular on employment outcomes. Garthwaite, Gross, and Notowidigdo (2014), study the effects of a public health insurance contraction in Tennessee on labor supply and ESHI. They find labor supply increases in response to a loss in public health insurance and that the increase is concentrated among individuals working more than 20 hours each week and seeking ESHI. McKearin (2015), studies the effect of a contraction in Missouri and finds employment increases on the extensive margin for part time workers and some parents are seeking out ESHI.

Many papers also try to determine the effects from public health insurance expansions on health and emergency room visits. Using the 2008 Oregon Medicaid Lottery, Taubman et. al. (2014) find expansions cause an increase in emergency room visits. Using the same lottery, Baiker et. al. (2013) find that while people reported feeling healthier, there were no significant improvements on measured physical health outcomes in the first two years. There was, however, a large and expensive increase in the use of health care services, increase in diabetes detection, and lower rates of depression amongst those who received Medicaid. Anderson et. al. (2014) find that as young adults lose health insurance, emergency room visits and hospital stays decrease. Coey (2015) finds a significant decrease in visits to health care providers as people lose Medicaid. Baldwin (1998) finds Medicaid expansion results in a decrease in the rate of low weight births.

Finally, many studies have focused on crowd-out estimates. Gruber and Simon (2008), survey the literature and find a range between 0% and 59% of crowd-out of private health insurance resulting from public health insurance. Garthwaite et. al. (2014) find a crowd-out of 59% amongst adults earning between 0% and 400% of the FPL. McKearin (2015) finds a range of crowd-out between 58% and 69% (though both values are statistically insignificant) for parents with a high school diploma or less. He finds a statistically insignificant crowd-out of 13% amongst all parents in Missouri.

This proposal contributes to the health insurance literature in many ways. First, I study Oklahoma, a state previously unstudied which includes a different group of adults than prior literature has focused on (my proposal focuses on adults making up to 200% of the FPL rather than just very poor adults, single mothers, childless adults, parents, or the elderly). Second, I study an expansion in ESHI. All studies reviewed focus on public health insurance expansions (e.g. Medicaid) and contractions. Since my study includes a state offering a subsidy for ESHI, it is, arguably, the most applicable estimate to understanding the effects of the private health insurance expansion we will see from the Affordable Care Act, that is, the portion of the Affordable Care Act that subsidizes individuals purchasing private insurance and penalizes employers who do not provide ESHI. Using data for the expansion that occurred from 2006 to 2009, I provide very recent estimates of what might happen to multiple important outcomes when the health insurance market is manipulated by the government.

My proposal provides support to many prior studies. Like Baicker et. al (2013), Decker and Selck (2012), Strumpf (2011), and the economists mentioned above who studied Seguro Popular, I find no significant employment changes due to the health insurance expansion. My proposal also provides support for Baicker, et al. (2013), Anderson et. al. (2014), and Taubman et. al. (2014) who find no significant health effects from the health insurance expansions but do find emergency room usage increases as health insurance coverage expands. My crowd-out estimates support the prior literature reviewed by Gruber and Simon (2008), though I study the crowd-out resulting from ESHI rather than the crowd-out resulting from public health insurance.

3. Insure Oklahoma

In response to a 2004 legislative directive, the Oklahoma Health Care Authority implemented Insure Oklahoma in November 2005.[76] Insure Oklahoma provided assistance to small firms to purchase health insurance on the private market for certain employees. Beginning in November of 2005, firms with 25 or fewer employees were provided with 65% to 85% of the premium costs for employees in household's earning less than 185% of the FPL and who did not qualify for Medicare or SoonerCare (the state's Medicaid program). Insure Oklahoma was and is financed by the state's tobacco tax.[77] Oklahoma's tobacco tax has been around since 1917 but was increased by 400% in 2004 to $1.03/pack. The funds were raised with the intention of funding several health care projects—one of them being Insure Oklahoma.[78]

Other requirements for firms to qualify for the subsidy included that they must also be located in Oklahoma, contribute at least 25% of the enrolled employees' premium costs, and offer a qualified health care plan. Employees must also be an Oklahoma resident, US citizen or legal alien, age 19-64, contribute up to 15% of the premium costs, and enroll in a qualified health plan offered by their employer. The premium assistance also covers spouses of the employees who meet the above restrictions (children would be covered by SoonerCare if parents met these requirements). Employees are also

---

76 All information in this section and in concern with Oklahoma's health insurance changes are found at Oklahoma Health Care Authority's website after scouring through archived annual reports located at: http://www.okhca.org/research.aspx?id=9662&parts=7447.

77 Information on the tobacco tax was pulled from the Oklahoma Policy Institute website at okpolicy.org.

78 Children with developmental disabilities were targeted to receive 40% of the funds. Insure Oklahoma was targeted to receive 33.5% of the funds. For more information, please see: okpolicy.org/files/tobacco_2010.pdf?635234.

responsible for deductibles and co-payments. By the end of fiscal year 2006, Insure Oklahoma had enrolled over 750 employees into an ESHI.

At the same time the subsidy for ESHI was implemented, SoonerCare (Oklahoma's Medicaid program) was expanded and heavily advertised. A family planning category, started in early 2005, was aggressively marketed throughout 2005 and resulted in an increase of 27,000 enrollees (from 3,000 to 30,000) by 2006. Also implemented in 2005 and heavily advertised throughout the year was a new category for women needing further diagnosis or treatment for breast and/or cervical cancer. This new category resulted in an increase from 1,600 to over 6,000 enrollees. Additionally, in late 2005, Oklahoma began enrollment for the Tax Equity and Fiscal Responsibility Act of 1982 as a means to further address the needs of disabled Oklahomans who would not otherwise qualify for SoonerCare benefits. Around this same timeframe, Oklahoma also worked with the Tobacco Settlement Endowment Trust to increase the use of the Oklahoma Tobacco Helpline services (a phone-based support and coaching program) by the SoonerCare population. A direct mailing to adults was successful in increasing utilization by almost 2,000 members. Not only did SoonerCare expand in enrollees during fiscal year 2006, but the reimbursement rate for providers was also increased.

Overall, the SoonerCare expansions included approximately 45,000 new enrollees in the state's Medicaid program; an increase of 6.5% from 2005 to 2006, much higher than any other years. This expansion of the public health insurance might hide (will definitely mute) the effects we might see on the crowd-out of public health insurance resulting from ESHI. Disentangling the effect of the expansion of SoonerCare on public health insurance from the effect of the expansion of ESHI that might cause a crowd-out in public health insurance will be one major task I accomplish in order to publish this proposal. I discuss this in further detail in the final section.

In fiscal year 2007, Insure Oklahoma made no major changes to the requirements firms and employees must satisfy to receive the subsidies for ESHI. However, an Individual Plan emerged in March 2007. The Individual Plan extended coverage to qualified individuals and groups by giving the same subsidy towards premium costs. The individuals and groups covered included uninsured self-employed individuals, employees whose firms did not provide health plans or who were not qualified to participate in their firm's health plan, sole proprietors not qualified for small group health plans, unemployed, and the disabled who were working. Specifically, the qualified individuals included self-employed people in households earning less than 185% of the FPL; employees working in a firm with 25 or fewer employees, in households earning less than 185% of the FPL, and who were ineligible for ESHI; temporarily unemployed individuals eligible for unemployment benefits; and working disabled people working for any size firm. Further, these individuals had to be ineligible for Medicare or SoonerCare. By the end of fiscal year 2007, more than 2,800 employees, spouses, and individuals had been enrolled in Insure Oklahoma and 1,030 businesses were participating in the plan. Unlike fiscal year 2006, SoonerCare did not have any significant changes among adult care.

More expansions occurred in fiscal year 2008 and 2009. In November of 2007, the number of employees a firm could have and still qualify for the subsidy increased as did the income threshold. Firms with 50 or fewer employees and employees in households earning less than 200% of the FPL could now qualify for Insure Oklahoma. The Individual Plan had the same two changes at the end of 2007 (in firms with 50 or fewer employees and in households earning less than 200% of the FPL). No other changes were made in fiscal year 2008. The main change in fiscal year 2009 applicable to this proposal was that firms could have up to 99 employees to qualify.[79]

By the end of fiscal year 2008, Insure Oklahoma enrolled over 11,600 employees, spouses, and individuals and had 2,742 businesses participating. By the end of fiscal year 2009, Insure Oklahoma had enrolled almost 21,600 individuals and had 4,752 businesses participating. The reason for such a large increase in enrollment in fiscal years 2008 and 2009 is credited to a media blitz the state launched in October 2007. Due to such drastic increases in 2008 and 2009, future versions of the analysis below may analyze the data treating 2008 as the initial post year. I may also extend the post years further out than 2009 since the program's initial start time and actual enrollment seem to be off by a few years. If extending past 2009, I will address possible concerns and admit to possible weaknesses since I might be allowing other factors to influence my results that I would be crediting to the subsidy.

Figure 3.1 depicts the enrollment in SoonerCare (the state's Medicaid program) and Insure Oklahoma. The data is aggregated at the annual level and comes from the historical annual report archives of the Oklahoma Health Care Authority (2015). Year is on the horizontal axis, the scale for total enrolled in SoonerCare is on the left hand side

[79] In 2009, Insure Oklahoma also began subsidizing private health insurance for full-time college students ages 19-22 in households making ≤ 200% of the FPL. 30 students were enrolled in fiscal year 2009.

vertical axis. This scale is used for the two lines labeled “Children ...” and the line labeled “SoonerCare …”. The scale for total enrolled in Insure Oklahoma is on the right hand side vertical axis and applies to the other four lines. Due to the way the data is reported in the archives, either total enrolled during the year or a value specific to enrollment in June only is reported in Figure 3.1. While the total enrolled in June is similar to the total enrolled throughout the year, it is slightly less. The total number of individuals enrolled in SoonerCare throughout the year is represented by the blue, big X marked line. The total number of children enrolled in SoonerCare in the month of June is represented by the red, small X marked line while the total number of children enrolled in SoonerCare throughout the year is represented by the green, small X marked line. In 2004, the annual report included both of these values but only reported total in June before 2004 and total for the year after 2004. The total enrolled in SoonerCare and the total number of children enrolled in SoonerCare follows a positive trend with no clear periods of increasing or decreasing enrollment. As described above, SoonerCare greatly expanded in 2006. While the slope from 2005 to 2006 for total enrolled in SoonerCare is a greater than the slope for the other years, the slope’s difference is statistically insignificant; therefore, it cannot be distinguished as being a greater increase from 2005 to 2006 than from any other pair of years.

Figure 3.1 also depicts the annual enrollment in Insure Oklahoma. Each of the values representing different groups of people for Insure Oklahoma is for the total enrollment in the month of June in the corresponding year. The total number of individuals enrolled in Insure Oklahoma in the month of June is represented by the yellow, square marked line. The total number of firms participating in Insure Oklahoma in the month of June is represented by the green, diamond marked line. The total number of individuals in Insure Oklahoma through their employer plan in the month of June (the initial one that came out) is represented by the red, triangle marked line. The total number of individuals in Insure Oklahoma through the Individual Plan in the month of June is represented by the purple, circle marked line. This figure supports the background discussed earlier. All the values are low in the initial years of 2006 and 2007. After 2007, there is a large increase in enrollment every year. Further, those enrolled in the Individual Plan follow a very similar trend to those enrolled in the employer sponsored plan, but almost 2 years delayed. Given that the individual plan started 1 year and 11 months later, this figure makes it appear that the individual plan enrolls about the same number of people as the employer plan, just 2 years delayed, probably due to the timing of the two programs.

Figure 3.2 focuses just on enrollment in Insure Oklahoma. The data, which comes from the Oklahoma Health Care Authority's *Insure Oklahoma* 2014 summary, is given monthly for the total number of enrolled individuals in and the total number of firms participating in Insure Oklahoma. Year is on the horizontal axis and total enrolled is on the vertical axis. Individuals enrolled in Insure Oklahoma are represented by the blue, open, circle marked line. Firms participating in Insure Oklahoma are represented by the red, filled, diamond marked line. The first red vertical line depicts the program's implementation, in November of 2005. The second red vertical line depicts the Individual Plan's implementation, in March of 2007. The third vertical line depicts the start of the media blitz (October 2007) that is credited with the large increase in enrollment in 2008 and 2009. Again the trends of the two lines follow the discussion in the prior paragraph. There is a slight increase in enrollment from the start of Insure Oklahoma through the start of the Individual Plan. Following the Individual Plan's implementation, enrollment for individuals begins to increase at a greater rate. Following the media blitz in October 2007, there is a drastic increase through the middle of 2010 where there seems to be a leveling off. Figures 3.1 and 3.2 establish the credibility of a first stage--that the subsidy did in fact lead to many people enrolling in ESHI. Figures 3.1 and 3.2 support using 2008 as the first post year in future implementations of this proposal.

4. Model

To align expectations of employment effects resulting from Oklahoma subsidizing employers offering ESHI to qualified individuals, I present a simple labor supply and demand model with one change in Figure 3.3. Labor demand represents the firm's demand of workers given they have to pay a certain wage and labor supply depicts the number of people willing to work at a certain wage. Total compensation, the one change I make to the normal labor model, is on the vertical axis (normally it is wage) and quantity of labor is on the horizontal axis. Labor demand, D_1, and supply, S_1, represent the demand and supply of labor prior to the subsidy and intersect to create equilibrium total compensation w* and employment N*. Assuming the market is in equilibrium prior to the subsidy, w* and N* are the total compensation and quantity of labor experienced in Oklahoma.

A government subsidy for firms providing ESHI has an effect on the firms and the workers. Firms have to pay a small portion (about 25%) of the ESHI and thus decrease the wage they are willing to pay the worker to compensate for this increase. However, the worker receives this slightly reduced wage plus ESHI and thus receives a net increase from his prior wage equal to this wage decrease plus the value of the subsidy to him. Assuming the value of the subsidy to the worker is greater than the decrease in the wage the firm pays, the resulting effect is that the total compensation to the worker increases. This positive net effect is represented by the shift in labor demand from D_1 to D_2 and results in an increase in the quantity of labor, from N* to N_σ. Firms are able to compensate the employee more than before despite actually paying a lower wage. Firms pay less to the employee, w_f instead of w*, but the worker receives more in total compensation, w_w instead of w*. $w_w – w_f$ equals the net value of the subsidy to the worker, that is, the excess of workers' valuation of ESHI over the employers' cost (net of subsidy) of ESHI, and is designated as σ. This graph shows a deadweight loss in the labor market. However, the overall gains to society may be greater than this loss; therefore, there may not be a deadweight loss to society overall because this subsidy deals with well-known problems in health insurance markets (e.g. adverse selection and imperfect competition) that lead to suboptimal take-up of insurance.[80] The model shows that, with the subsidy offered by Oklahoma to firms offering ESHI and assuming the value of the subsidy to employees is greater than the wage decrease from firms, employment should increase and total compensation should increase. The increase in

[80] This offers a ripe opportunity for future research.

employment could be along the extensive or intensive margin. Empirical strategies and estimations allow us to determine the exact effects.

5. Data and Empirical Strategy

5.1 Data

For this research, I use the Integrated Public Use Microdata Series (IPUMS) to gather data from the Current Population Survey (CPS). Specifically, I use the CPS March supplemental surveys from the years 2000 to 2010 as they contain additional information on income, poverty, and health insurance. Since the state of Oklahoma provided subsidies to firms providing ESHI to employees who were ages 19 to 64 (among other requirements), I classify adults as those who are ≥ 19 years old and remove anyone who is not an adult from the dataset. To prevent confounding my results with evidence from Medicare or Tricare (the military's health insurance plan) and to mitigate the survey response errors, I remove anyone over the age of 65 and anyone serving in the military.[81]

The health insurance questions that pertain to the years 2000 to 2009 come from the 2001 to 2010 March CPS surveys because health insurance questions ask about coverage in the previous year. I use the health insurance sample weights from the CPS for the health insurance variables in all but the non-weighted regressions.[82] I classify

[81] In principle, I should also eliminate pregnant women, blind individuals, and retired veterans who may be eligible for Tricare. I do not see that information in my data and I also assume those groups that are interviewed are very small. By not eliminating them from the data, I am biasing my results to finding no effect.

[82] While not shown, regressions not weighted are available upon request. Results are similar to the weighted regressions.

individuals as having PUHI if they claim to have any type of public health insurance.[83] I classify individuals as having employer sponsored health insurance if they claim to have insurance through their employer. I classify individuals as having private health insurance if they claim any type of private health insurance.

The employment information and self-reported health status for the years 2000 to 2009 comes from the 2000 to 2009 March CPS surveys and pertains to the survey reference week. I classify someone as working if they are at work during the survey reference week. The reported health status is on a scale of 1 to 5 with 1 being excellent and 5 being poor. For employment and health status, I use the person-level weights from the CPS supplement in all but the non-weighted regressions.

The emergency room visits per 1,000 people comes from the Kaiser Family Foundation website, located at: http://kff.org/other/state-indicator/emergency-room-visits-by-ownership/. The data is given in aggregate each year for each state from 1999 on. This data set is merged with the CPS data after aggregating at the state level and applying the appropriate CPS weights. Unlike the CPS data, the Kaiser data includes all individuals in the state. Therefore, it includes children under the age of 19, adults from 19-64, elders over age 64, and individuals in the armed forces.

[83] I classify PUHI in this way as opposed to those on Medicaid because many states have names for their Medicaid program. For example, Oklahoma calls hers SoonerCare, Missouri calls hers MOHealthNet, and Tennessee calls hers TennCare. Thus, in a survey, someone might claim to have public health insurance but not Medicaid, even though they actually do have Medicaid. Since I have eliminated all military personnel and people 65 or older, I have effectively eliminated anyone with Tricare or Medicare – except those who are disabled or retired military. The few people I am picking up under these two programs or other public health insurance programs by classifying as I have creates a trivial, if any, amount of noise.

Table 3.1 presents summary statistics for the group that is left in Oklahoma from 2000-2005 (adults age 19-64 and not in the military). The second column, labeled Oklahoma, includes the sample in Oklahoma. The South Region includes the states that IPUMs defines to be in the southern region and are used as the controls throughout the study.[84] The final column, labeled Difference, displays the absolute value of the difference between the average percentage in Oklahoma and the average percentage in the states in the South Region. Within this group, Oklahoma, when compared to the South Region, only really appears to be different in race composition. Oklahoma has fewer blacks and more adults of other races. All other values are very similar.

5.2 Empirical Strategy

I take advantage of the across-state variation that occurred when Oklahoma began offering a subsidy to employers offering ESHI which resulted in over 21,000 people gaining ESHI by June of 2009. I perform many DD regressions after aggregating at the state-year level without any control variables to highlight that the statistical significance of my results do not depend on including individual-level covariates.[85] I exploit the fact that Oklahoma had a subsidy offered in November of 2005 that affected adults in Oklahoma. My aggregate DD regression takes the following form:

$$y_{st} = \alpha_s + \alpha_t + \beta * \mathbb{1}_{s=OK} * \mathbb{1}_{t\geq 2006} + \epsilon_{st}. \quad (1)$$

---

[84] The IPUMs defined "South Region" includes the following states: Maryland , North Carolina, South Carolina, Virginia, West Virginia, Delaware, Florida, Georgia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas.

[85] Results with covariates included in the regressions are very similar to without. Results are available upon request.

$y_{st}$is the outcome of interest in state s at year *t*. α_s are state fixed effects and α_t are year fixed effects. The indicator variable $\mathbb{1}_{s=OK}$ takes on a value of 1 if the state is Oklahoma (which is the treatment group) and 0 otherwise. The indicator variable $\mathbb{1}_{t\geq 2006}$ takes on a value of 1 if the year is 2006 or greater and 0 otherwise (to capture post implementation). The error term ϵ_{st} accounts for the effect of all unobserved variables which vary over state and time and is assumed to be uncorrelated with all observables. The parameter of interest is β. β identifies the impact of the subsidy on the outcome variable. A value of $\beta = 0.03$ would be interpreted as follows: a 3 percentage point change for adults in Oklahoma relative to adults in the control group. For ease of reading, I will not refer to this interpretation every time but will instead just state the percentage point change. However, I always mean relative to the interpretation just described. This DD regression controls for any unobservable common shocks that affected all adults across the country in a given year. The key identifying assumption for the DD is that outcomes for adults in Oklahoma would have evolved in a similar fashion to the outcomes of other adults in the control states, absent Insure Oklahoma.

The main outcomes of interest (dependent variables) are share of people with employer sponsored health insurance (ESHI), with private health insurance, with public health insurance, and employed. Additionally, self-perceived health status and emergency room visits per 1000 people are analyzed. Due to the subsidy, I expect β to be positive for ESHI, private health insurance, and employment. As explained in the introduction, I expect public health insurance to be weakly negative and do not have expectations for self-reported health status or emergency room visits. For this proposal, I report standard errors after clustering at the state level. Should I pursue publication, I will perform the modified two-stage block bootstrap described in McKearin (2015).

6. PRELIMINARY RESULTS

In this section, I present my preliminary results. I first report results from the subsidy on health insurance. Second, I calculate crowd-out estimates from these results. Finally, I analyze effects on health, emergency room usage, and employment.

6.1. Effects on Health Insurance

Figure 3.4 presents the share of residents who report being employed with ESHI. Share employed with ESHI is on the vertical axis and two-year binned means are on the horizontal axis (given the small cell sizes, I group the respondents into two-year bins in the figures but run all regressions with years individually). The blue, X marked line displays the adult population in Oklahoma (the treated group). The red, diamond marked line depicts the adult population in the South Region. Importantly for the DD regression, the two lines follow the same trend prior to the subsidy being offered. There is a clear break and reversal of this trend between Oklahoma and the South Region after the subsidy is offered. Oklahoma has a large increase in share employed with ESHI immediately following the subsidy offering, and then maintains a slight increase into the 2008-2009 year bin. The South Region experiences a slight decrease immediately following the subsidy, and a sharp decrease into the last year bin.

The figure lines up with expectations. We expect adults in Oklahoma to experience an increase in ESHI following implementation of the subsidy. Due to the 2008 recession, we know many people became unemployed between 2008 and 2009.

Therefore, we expect to see a decrease overall in employed with ESHI due to this event but, in Oklahoma, we see an increase. It appears the recession did halt the increase of ESHI but Insure Oklahoma may have been the reason there is still a slight increase. The picture for the southern states satisfies expectations once realizing the recession probably led to much of the decrease in ESHI in the southern states. In light of the 2008 recession, Insure Oklahoma appears to have allowed many Oklahomans to maintain health insurance.

Table 3.2 presents regression estimates of equation (1) using data from the CPS. Each column in the table represents a different regression according to equation (1), with the different dependent variables listed in the top row of each column. Each row gives the statistics listed on the left hand side of the table for the dependent variable labeled at the top of the column.[86] As described earlier, standard errors are calculated by clustering at the state level.

Column 1 of Table 3.2 presents the estimates for share employed with ESHI. Adults in Oklahoma experience a 3.72 percentage point increase in ESHI, relative to adults in the South Region. Statistically significant at the 1% level and taking into account the mean of the share employed with ESHI, this change translates into more than a 7% increase in Oklahoma residents employed with ESHI, which roughly lines up with Figure 3.4.

Figure 3.5 presents the share of residents who report having any private health insurance. ESHI is a subset of the people having any private health insurance and thus

[86] All variables but the variable of interest are excluded for ease of readability.

we expect Figures 3.4 and 3.5 to be similar. Except for the vertical axis now representing the share reporting any private health insurance, the format is the same as Figure 3.4. The trend is roughly the same before the subsidy is offered but, again, the two lines break this trend following the subsidy. Oklahoma has a slight decrease immediately following the subsidy but a large increase into the last two years. The southern states see a very small decrease followed by a large decrease in the years 2008 and 2009. The prior discussion about the 2008 recession only strengthens this figure's support that Insure Oklahoma had a positive effect on adults gaining private health insurance.

Table 3.2, column 2 depicts regression estimates of equation (1) for the share who have any private health insurance. Again significant at the 1% level, the equation estimates there to be a 3.1 percentage point increase among adults in Oklahoma with any private health insurance. Taking into account the mean of the dependent variable, a 3.1 percentage point increase equates into approximately a 4.9% increase among adults in Oklahoma. According to the U.S. Census Bureau, Oklahoma had approximately 2,177,193 people ages 19-65 in 2005.[87] A 3.10 percentage point increase equates to almost 67,400 people gaining any private health insurance. By March of 2009 (when the CPS survey is given), the Oklahoma Health Care Authority reports that 17,486 people were enrolled in Insure Oklahoma. The difference in magnitude between the two numbers is almost four-fold. Such a disparity warrants further investigation as I move

[87] The US Census Bureau reported 3,547,884 people with 24.1% of them being under age 18 and 13.2% being age 65 or older. Splitting each age bin between ages 18 and 65 uniformly eliminates an additional 1/47 of the remaining group resulting in the 2,177,193 number. Realize, this value includes people in the military; therefore, it is higher than my actual base number as Oklahoma has quite a few Air Force bases and Army posts.

forward with the analysis. Here, I note that the clustered standard errors are probably not conservative enough because of the aggregation at the state level that I use for inference. Clustering with aggregate level data does not account for sampling error in cell means and may therefore not be accurate in small samples (Garthwaite, Gross, and Notowidigdo, 2014). Performing the two-stage block bootstrap as specified in McKearin (2015) addresses this concern and will be performed in future iterations of this proposal.

Figure 3.6 presents the share of residents who report having any public health insurance. Except for the change of the variable on the vertical axis (now it is the share reporting any public health insurance) the format is the same as Figures 3.4 and 3.5. The trend is almost exactly the same before the subsidy is offered but, again, the two lines break this trend following the subsidy. Oklahoma experiences a significant increase immediately following the subsidy but a slight decrease in the last two years. This is opposite to what we expect to occur if we expect a crowd-out of public health insurance from a subsidy offered on ESHI. However, the increase in the 2006-2007 year bin lines up with expectations given the information in the background section about the expansion of SoonerCare (the state's Medicaid program) that occurred in fiscal year 2006. Disentangling the effects on SoonerCare resulting from the public policies that expanded public health insurance from the ones that implemented a subsidy for ESHI is a major improvement I hope to make in future iterations of this proposal. Since the net effect from 2006 to 2009 is an increase in SoonerCare, it appears the policies expanding health care have a greater impact than the subsidies that might decrease health care; determining the effect of each individually will greatly enhance a future paper.

Figure 3.6 also suggests that using 2008 and 2009 as post years (as mentioned earlier) might show a greater impact from the subsidies on health care. The southern states experience no change immediately following the subsidy and a drastic increase into the last two years (probably due to the recession). Table 3.2, column 3 depicts regression estimates of equation (1) for the share who have any public health insurance. The results are not surprising given Figure 3.6 and the discussion about the expansion of SoonerCare in the background section. The coefficient is insignificant, economically and statistically. While a magnitude cannot be estimated at this point, the results do lend support that Insure Oklahoma caused a decrease in Oklahomans covered by public health insurance. As explained in the Insure Oklahoma section, we know Oklahoma experienced a large increase in Medicaid enrollment in 2006, almost 45,000 new enrollees and a 6.5% increase from 2005. Given this information, it seems we should find an increase in people having public health insurance. The fact that this coefficient is statistically insignificant and appears to equal zero could mean that Insure Oklahoma actually moved people out of SoonerCare. At this point I cannot separate the two effects; therefore, my estimates undoubtedly show the combined effect resulting from the expansion of SoonerCare and implementation of Insure Oklahoma.

Crowd-out estimates of private and public health insurance resulting from ESHI can be calculated using the coefficients from regression equation (1) for these three variables. It does not appear there is any crowd-out of public health insurance by ESHI.[88] The value is statistically insignificant but does suggest a crowd-out of approximately

[88] The same discussion about a possible effect described in the preceding paragraph applies here too.

14.5% ($\beta_{public}/\beta_{ESHI}$). This is unsurprising since one of the rules for receiving the subsidy included that the adult qualifying for the subsidy of ESHI had to be ineligible for SoonerCare or Medicare. Since these are the two largest public health insurance programs in the state, it makes sense that we might not see any (or would only see minimal) crowd-out of PUHI.[89]

We also see a small and statistically insignificant crowd-out of other forms of private health insurance from ESHI. ESHI is a subset of private health insurance. It is possible that some people went from having some type of private health insurance to having ESHI and thus dropped their original private health insurance. I calculate a statistically insignificant crowd-out of approximately 4%.[90] That is, approximately 4% of the people who gained ESHI dropped another form of private insurance (4% is merely suggestive). Since there was at most a 14.5% crowd-out of public health insurance (and a statistical insignificance that prevents me from rejecting the value is equal to 0) then somewhere between 81% and 100% of the people who gained ESHI had no insurance beforehand. The switch of these people who had no health insurance to now having health insurance may benefit society.

6.2. Effects on Self-Reported Health, Emergency Room Usage, and Employment

Figure 3.7 presents the share of residents who report being employed. Except for the vertical axis now representing the share employed, the format is the same as Figure

---

[89] Two examples of people who might pick up ESHI due to the subsidy but had SoonerCare or Medicare prior to it include children who turned 19 and thus lost SoonerCare but met the qualifications to receive ESHI and disabled adults who disqualified themselves from Medicare by working.

[90] I calculate this value by regressing equation (1) with the dependent variable being the share who report having private health insurance that is not ESHI ($\beta_{private\_no\_ESHI}$). The corresponding value is a statistically insignificant -0.00151. Dividing $\beta_{private\_no\_ESHI}$ by β_{ESHI} results in the reported value.

3.4. The trend of the two lines in the pre period is not similar. This breaks one of the necessary conditions when performing a difference-in-difference regression of needing trends the same before the treatment so that the two groups can be compared after the treatment. With trends being different in the pre period, there is no reason to believe that the two would have behaved the same after the subsidy was offered. Even more puzzling is that it appears employment decreases in Oklahoma after the subsidy is offered.[91] Theory shows that we should see an increase in employment, but the empirics clearly do not support the theory in this case.

Table 3.2, column 4 depicts regression estimates of equation (1) for the share employed. The value is both statistically and economically insignificant; therefore, we fail to reject that the coefficient is equal to 0. Realize though, the coefficient should be interpreted with caution since the figure does not support the use of a DD regression. While theory shows an increase in employment will occur due to the subsidy on ESHI, prior studies analyzing health insurance expansions found no labor market effects resulting from such an expansion.[92] The results using the CPS data support those authors' findings. In future iterations of this paper, I will use the ACS instead of the CPS for the employment information. Since the ACS has many more observations, the results are more reliable and will either confirm the CPS findings or perhaps support the theory and show employment in fact increased for parents in Oklahoma.

---

[91] This could be happening due to the expansion in Medicaid and possible resulting decrease in labor supply (as found in McKearin (2015) and Garthwaite et al (2014).

[92] See Baicker et. al (2013), Decker and Selck (2012), Strumpf (2011), and the economists mentioned in the Insure Oklahoma section who studied Seguro Popular.

Figure 3.8 presents the average of the self-reported health status of the CPS respondents. Except for the change of the variable on the vertical axis (it is now the average of self-reported health status) the format is the same as Figure 3.4. A scale of 1 to 5 is used for self-reported health status with 1 being excellent health and 5 being very poor health. The trend of the two lines in the pre period is not similar and thus the same problem arises as with the employment figure and the use of a DD regression. Also interesting, the figure shows that the self-reported health status following the subsidy increased in Oklahoma, which means the self-reported health status of Oklahoma adults worsened after the subsidy. The coefficient in Table 3.2, column 5, indicates a statistically significant decrease in health status (positive coefficient) for adults in Oklahoma. As before, the coefficient is not reliable since the figure does not support using a DD regression and thus it is only suggestive in nature. As mentioned in the introduction, a decrease in self-reported health status may indicate that people have become more aware of their poor health status since gaining health insurance or that moral hazard has occurred.

Figure 3.9 depicts the number of emergency room visits per 1,000 people. Except for the vertical axis now representing emergency room visits per 1,000 people, the format is the same as Figure 3.4. Unlike the previous two figures, the two lines follow the same trend prior to the subsidy being offered. After the subsidy, the number of emergency room visits increases drastically for the adults in Oklahoma but only slightly for the adults in the southern states. Recall, the data for this figure comes from the Kaiser Family Foundation and is representative of the entire population of Oklahoma and the southern states. It does not focus in on adults ages 19 to 64 who are not in the armed forces.

Remember, at the same time Insure Oklahoma was introduced, SoonerCare was also expanded. Taubman et. al. (2014) find that emergency rooms visits increase as Medicaid expands. While the coefficient for self-reported health status may equal 0, it is suggestive that adults in Oklahoma experienced a decrease in health status. Taubman et. al.'s (2014) findings along with the suggestive decrease in health status of adults in Oklahoma both support emergency room visits increasing in Oklahoma around the same time the subsidy was offered (and SoonerCare was expanded). Again, in future iterations of this paper I hope to try and disentangle the effects of policies that expanded SoonerCare at the same time an ESHI subsidy was offered.

Table 3.2, column 6, depicts regression estimates of equation (1) for the number of emergency room visits per 1,000 people. Significant at the 1% level, the equation estimates there to be an increase of almost 55 visits per 1,000 people in Oklahoma. Another possible explanation for such a large increase not mentioned in the Insure Oklahoma section was that, in 2007, Oklahoma increased the income limit to qualify for SoonerCare for children ages 0 to 19 to include children in families earning less than 300% of the FPL (previously it had been 185%). Such a change could also lead to an increase in emergency room visits, given Taubman et. al.'s (2014) findings.

7. Plans for Future Implementation (after dissertation is complete)

In this section I outline my plans for future implementation of the paper to work on after my dissertation is complete and before trying to publish it.

One main result I want to explore is the result on the employment effects and hopefully come up with estimates of the firm's payroll elasticity of hiring workers. In this proposal, I have used the CPS to determine employment effects. In future iterations, I will use the American Community Survey (ACS) in order to see the effects. The ACS has many more observations each year and thus has more precise results. Using the ACS, I hope to find employment in fact increased around this same timeframe. If I still find no change in employment, I will not be able to calculate a payroll elasticity but will confirm the robustness of the results presented earlier. However, if I find a change in employment then I can calculate the payroll elasticity of hiring workers.

The elasticity equation that would be simplest to estimate will be to run a regression with natural logs and then calculate the payroll elasticity of hiring workers as:

$$\Delta\ ln\ (employment\ increase) / \Delta\ ln\ (wage) \qquad (2)$$

I will have the employment increase and wage change the employee reports from the ACS data (and CPS data). As shown in the model section and assuming the employee values the subsidy, the worker's total compensation would be higher than this wage change. Since I know the initial equilibrium point (in actuality I assumed it to be the value in the pre period), then I can calculate the payroll elasticity of hiring workers using the demand side of the equation but will be unable to calculate the labor supply elasticity using the supply side since I do not know the value of the subsidy to the employees.

Another major advancement I hope to make in the future is one I have mentioned a few times throughout this proposal. I need to disentangle two effects. Public policies that expanded many facets of SoonerCare (Medicaid) were implemented in fiscal year

2006 (and were explained in the Insure Oklahoma section). These policies should have the effect of expanding enrollment in SoonerCare and possibly effecting employment outcomes. Also in fiscal year 2006, a subsidy was offered to employers offering ESHI (the main policy studied and explained throughout this proposal). As explained in the introduction, this subsidy should either have no effect on public health insurance or cause a crowd-out of public health insurance (i.e. a decrease in enrollment in SoonerCare). As explained in the model section, the subsidy should also increase employment. Separating these two effects, the increase in enrollment of public health insurance resulting from the policies expanding SoonerCare and the decrease we might see in public health insurance resulting from the subsidy to employers for ESHI is of prime importance. Equally important is disentangling these two effects on their labor market outcomes. Calculating the effect from the subsidy and relating it to the effects we can expect to see from the Affordable Care Act provides policy makers with accurate information to use to prepare for side effects from the Act.

Currently, I see two ways to try to disentangle the two effects. One way is to avoid using 2006 as the initial post year. Instead, I could use 2007 or 2008 as the initial post year. This will allow SoonerCare's 2005 and 2006 expansion to run its course and also allow Insure Oklahoma to establish credible enrollment rates. As discussed in the Insure Oklahoma section, Insure Oklahoma saw an enrollment increase of 750, 2,800, and 11,600 in fiscal years 2006, 2007, and 2008 respectively. While the subsidy program was implemented in November of 2005 and expanded in March and November of 2007, the actual take up of the subsidies did not begin to occur in mass until the beginning of

2008 (refer to Figure 3.2). Since the SoonerCare expansion was complete by the end of 2006, the effects using 2007 or 2008 as post years would be solely from Insure Oklahoma (but might be complicated by the recession). Moving the post years further out than 2006 provides one way to try and disentangle the effects of SoonerCare from Insure Oklahoma.

A second way that may enable me to disentangle the two effects takes advantage of enrollment criteria in SoonerCare (the state's Medicaid program). Medicaid in Oklahoma (and most states) covers pregnant women and children who make up to 185% of the FPL. Additionally, it covers non-pregnant adults with children who make below 37% or 57% of the FPL (depending on the year). In 2005, amongst other things, it added in a family planning category that was responsible for most of the increase in 2005 and 2006 (27,000 extra enrollees). Anyone who does not have a child has probably never taken advantage of Medicaid (two examples of possible exceptions include a pregnant lady who miscarried or a woman with breast cancer). People with children are more likely than people without children to have been enrolled at some point in SoonerCare. Since people without children are highly unlikely to ever have been in SoonerCare, using this group to try and tease out the effects of Insure Oklahoma may prove fruitful. In future work on this proposal, I will eliminate all people with children from my data and perform a DD regression using only people without children. In the same vein, difference-in-difference-in-difference regressions with the third variable on the interaction term being adults with children could also be run. Taking advantage of the fact that childless adults have likely never been on SoonerCare, these regression estimates might avoid effects from the state's Medicaid program.

The last major advancement I may pursue is to explore further the people who switch from having no health insurance to having employer sponsored health insurance in order to calculate the net benefit society gains from this policy. Exploring this further will reveal important effects the Affordable Care Act might have. In this proposal, I determine a large number of people who gained ESHI had no insurance beforehand. One main reason the Affordable Care Act was implemented was because of a belief that benefits from having everyone in the nation on some form of health insurance. The benefit of people having health insurance probably has a monetary value associated with it. I will review the literature to see if I can determine the value society obtains from someone acquiring health insurance who previously did not have it. The subsidy Oklahoma provided clearly has a cost associated with it – a monetary one I should be able to find, calculate, or come up with using a "back-of-the-envelope" calculation. Since I know the number of people who enrolled in Insure Oklahoma by the end of fiscal year 2009, I can use the benefit and the total costs I find/calculate to calculate the net social benefit from the program. Providing such estimates will greatly support (or refute) implementation of Insure Oklahoma and the Affordable Care Act.

I hope to make some smaller changes to the proposal. Similar to McKearin (2015), I will calculate the standard errors using the two-stage block bootstrap method (which I avoided due to the time required to calculate such standard errors). I will also see if I can find a better proxy for health than self-reported health status and emergency room visits. I am confident other proxies exist but I know I cannot use the most commonly used health status indicator of low birth weight since the Oklahoma subsidy did not impact pregnant women. I also cannot use another very common one, life expectancy, since Insure Oklahoma did not affect elders. I hope to find values for blood pressure, cholesterol, diabetes, obesity, or other indicators that might help determine if the health status of adults in Oklahoma improved following the offering of the subsidy. I will also look for other sources of emergency room visits since I am perplexed by the findings reported by the Kaiser Family Foundation. As seen in Table 3.2, column 6, the mean for emergency room visits according to the Kaiser Family Foundation for the south region from 2000 to 2009 is 450 visits per 1,000 people. This value seems very high and I hope to validate its reporting with another data source. Further, I will add standard error bands to Figures 3.4 to 3.9, the ones that depict the means of the dependent variable of interest for the southern states and Oklahoma, in order to see if pre trends are significantly different.

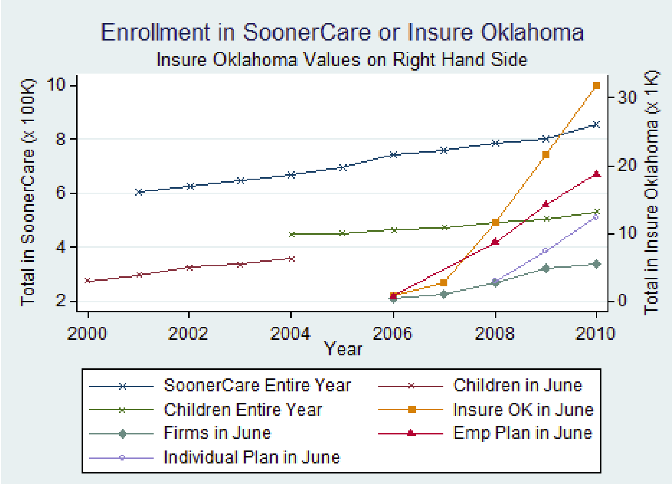
I will perform state and year robustness checks in future iterations. While not reported in the proposal, I already have checked the results using three other sets of controls: using all 50 states, only using the states that did not have a public health insurance contraction, and only using the states that border Oklahoma. The results are very similar using these other controls. In order to provide more robustness to my results, I will vary the years of implementation to see if I get the supporting results. I will also perform state falsification tests. The state falsification tests I will perform will be to re-run regression equation (1) but change out the treated state to be one of the control states instead of Oklahoma. I will do this for each state that is a control while keeping the other control states as the controls. This will result in a coefficient for each control state for each dependent variable of interest. I will then compare these coefficients to the coefficients for Oklahoma to see if other states give me the same or similar results. Hopefully, other states do not have such large effects and the coefficients for Oklahoma are much different than the coefficients for the other states. If other states give similar results to Oklahoma, then the causal interpretation of the subsidies' effect become less valid.

Finally, I will run a few other robustness checks. I will estimate results after narrowing in on the income levels of the people who should be affected (those in households earning less than 200% of the FPL). Specifically, I will remove everyone making greater than 200% of the FPL and run regression equation (1). I should see larger results of ESHI changes when I do this and will check to see if the income distribution changed in order to help mitigate endogeneity concerns when using income as a way to narrow in on my observations. I will also run triple difference regressions that take the following form:

$$y_{stp} = \alpha_s + \alpha_t + \alpha_p + \gamma_{st} + \gamma_{sp} + \gamma_{pt} + \delta * \mathbb{1}_{s=OK} * \mathbb{1}_{t\geq 2006} * \mathbb{1}_{p\leq 200\%} + \epsilon_{stp}. \quad (3)$$

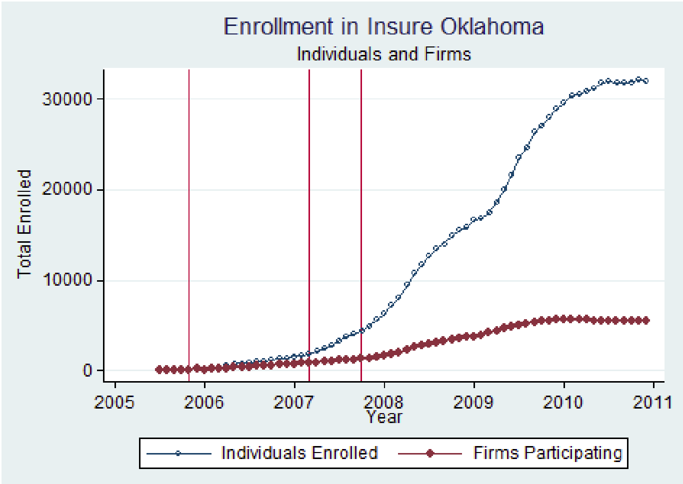
y_{stp} is the outcome of interest in state *s* at year *t* with income level *p* (which is equal to 1 if the adults live in a household making less than 200% of the FPL and 0 otherwise). α_s are state fixed effects, α_t are year fixed effects, and α_p are income level fixed effects. γ_{st} are all the state-time pairwise interactions, γ_{sp} are all the state-income pairwise interactions, and γ_{pt} are all the income-time pairwise interactions. The indicator variable $\mathbb{1}_{s=OK}$ takes on a value of 1 if the state is Oklahoma (which is the treatment group) and 0 otherwise. The indicator variable $\mathbb{1}_{t\geq 2006}$ takes on a value of 1 if the year is 2006 or greater and 0 otherwise (to capture post implementation). The indicator variable $\mathbb{1}_{p\leq 200\%}$ takes on a value of 1 if the adults live in a household making less than 200% of the FPL and 0 otherwise. The error term ϵ_{stp} accounts for the effect of all unobserved variables which vary over state, time, and income status and is assumed to be uncorrelated with all observables. The parameter of interest is δ. δ identifies the impact of the subsidy on the outcome variable. A triple difference equation like equation (3) is often used as a robust check to the DD equation (1). It provides support to my regression estimates as long as the absolute value of δ is greater than the absolute value of β.

Figure 3.1: Annual Enrollment in SoonerCare and Insure Oklahoma



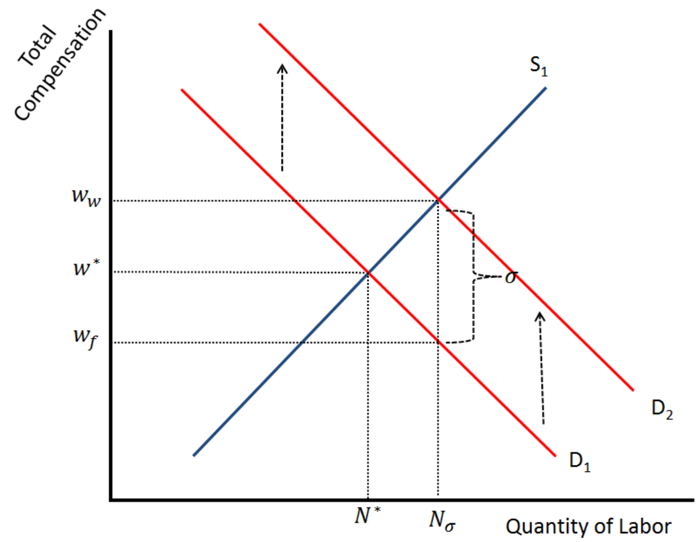
Notes: The figure above represents the total number of individuals enrolled in SoonerCare and Insure Oklahoma. The aggregate data is provided by the Oklahoma Health Care Authority (2015). Year is on the horizontal axis. The scale for total enrolled in SoonerCare is on the left hand side vertical axis and total enrolled in Insure Oklahoma is on the right hand side vertical axis. The lines labeled "… Entire Year" represent the total enrollment for the entire year. The lines labeled "… in June" represent the total enrolled in the month of June (which is slightly less than the total enrolled in the entire year).

Figure 3.2: Monthly Enrollment in Insure Oklahoma



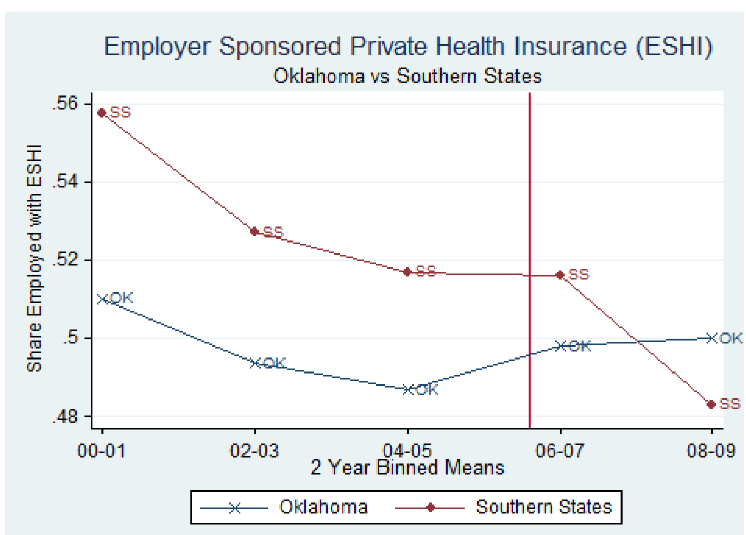
Notes: The figure above depicts the enrollment in Insure Oklahoma. The monthly level data is provided by the Oklahoma Health Care Authority (2015). Year is on the horizontal axis. The total enrolled in Insure Oklahoma is on the vertical axis. The first red vertical line depicts the program's implementation (November 2005). The second red vertical line depicts the Individual Plan's implementation (March 2007). The third vertical line depicts the start of the media blitz (October 2007) that is credited with the large increase in enrollment in 2008 and 2009.

Figure 3.3: Labor Demand and Supply



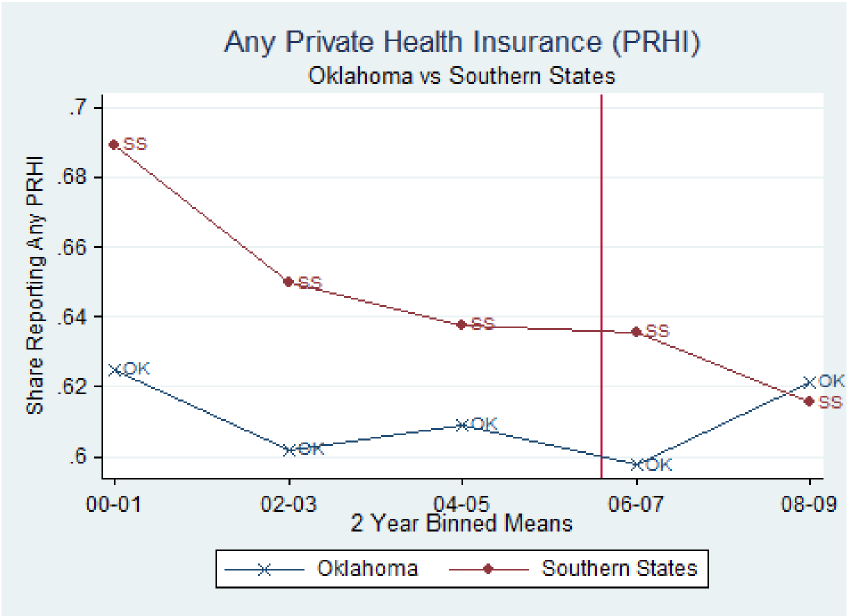
Notes: The figure above depicts a basic labor market. Total compensation is on the vertical axis and quantity of labor is on the horizontal axis. The value of the subsidy to the employees offered by the state of Oklahoma is represented by σ. The red lines, D_1 and D_2, represent the labor demand before and after Oklahoma offered the subsidy. The blue line, S_1, represents the labor supply.

Figure 3.4: Employer Sponsored Health Insurance



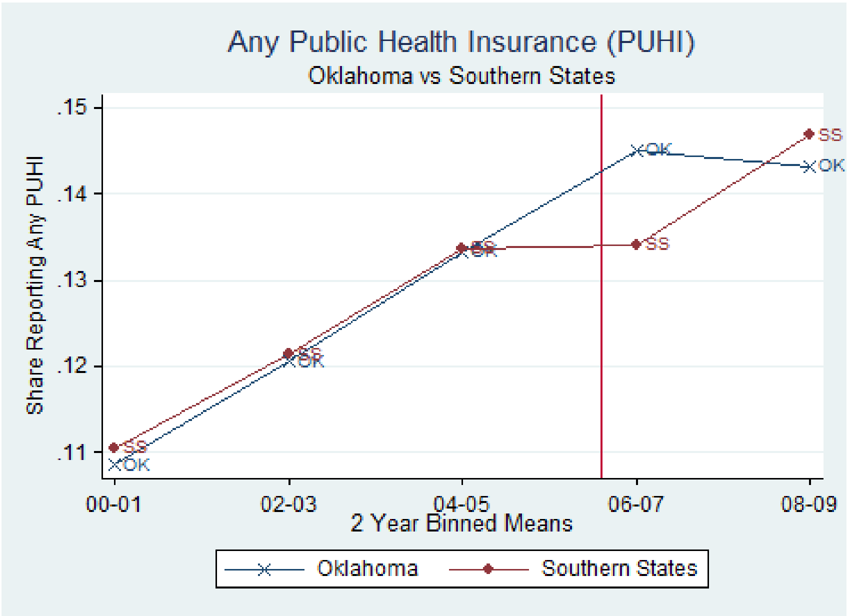
Notes: The figure above represents the share of CPS March respondents ages 19-64 and not in the armed forces who report being employed with employer sponsored health insurance. The figure presents means by 2-year cells, using the appropriate CPS provided weights. The red line, labeled SS, represents the average of the Southern States/South Region as defined by IPUMS.

Figure 3.5: Private Health Insurance



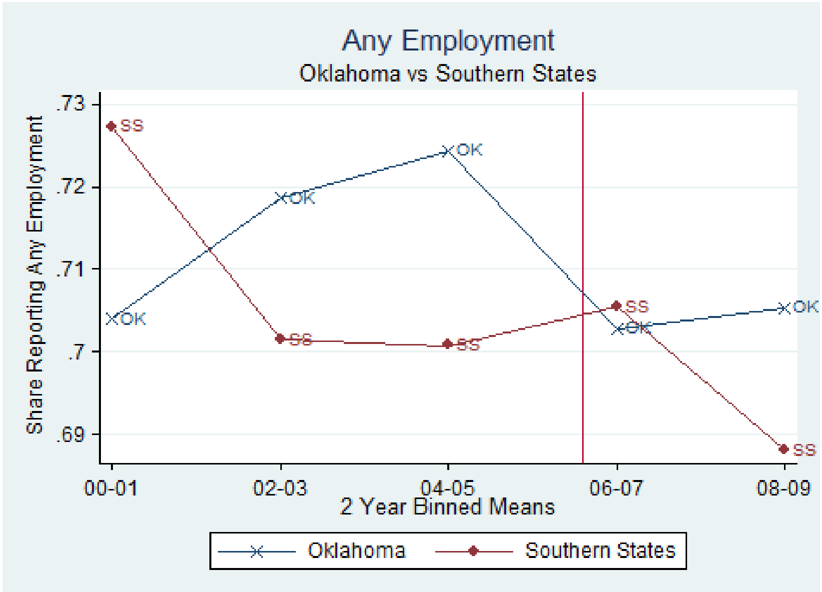
Notes: The figure above represents the share of CPS March respondents ages 19-64 and not in the armed forces who report having any private health insurance. See Figure 3.4's notes for more details.

Figure 3.6: Public Health Insurance



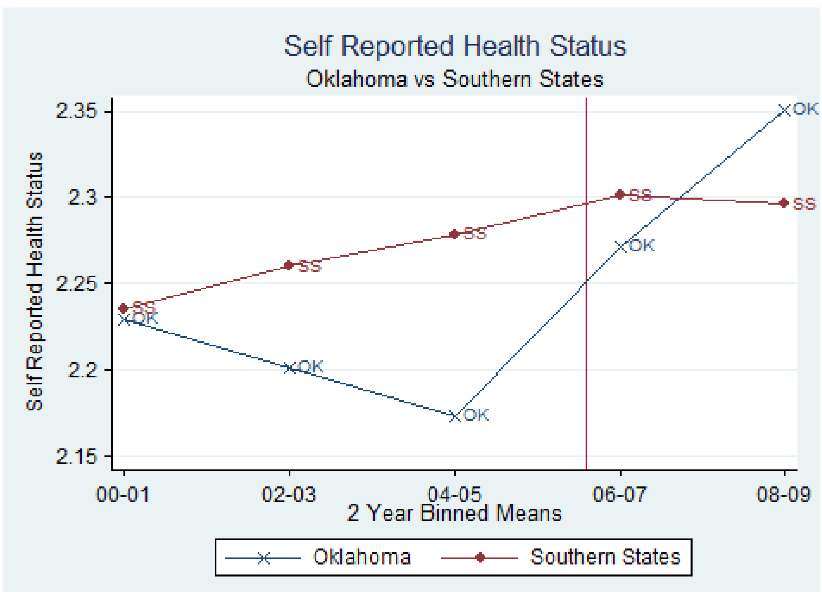
Notes: The figure above represents the share of CPS March respondents ages 19-64 and not in the armed forces who report having any public health insurance. See Figure 3.4's notes for more details.

Figure 3.7: Employed



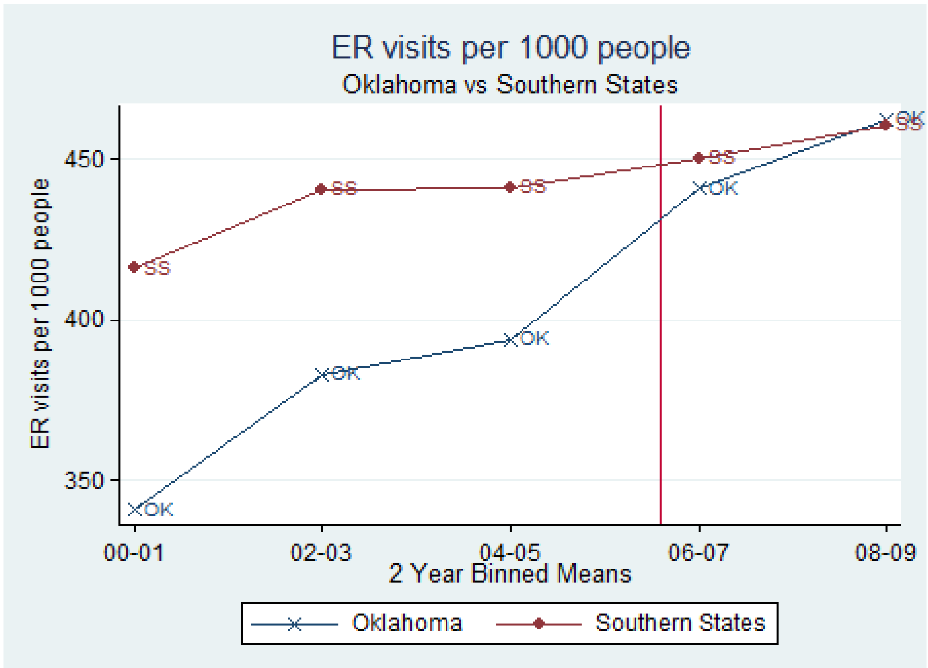
Notes: The figure above represents the share of CPS March respondents ages 19-64 and not in the armed forces who report being employed. See Figure 3.4's notes for more details.

Figure 3.8: Self-Reported Health Status



Notes: The figure above represents the average of the self-reported health status by the CPS March respondents ages 19-64 and not in the armed forces. The range reported is between 1 and 5 with 1 being excellent and 5 being very poor. See Figure 3.4's notes for more details.

Figure 3.9: Emergency Room Visits



Notes: The figure above represents the number of Emergency Room visits per 1,000 people according to the Kaiser Family Foundation. Unlike the prior figures, this figure does not eliminate anyone from the data. The figure presents means by 2-year cells. Like the prior figures, the red line, labeled SS, represents the average of the Southern States/South Region as defined by IPUMS.

Table 3.1: Summary Statistics

	Oklahoma	South Region	Difference
Any ESHI	49.66%	52.11%	2.45%
Any Private Health Insurance	61.21%	64.32%	3.12%
Any Public Health Insurance	12.10%	11.08%	1.01%
Age between 40 and 64	51.90%	51.54%	0.36%
White	80.67%	77.47%	3.21%
Black	7.58%	18.79%	11.21%
Other	11.75%	3.74%	8.01%
High School Dropout	11.46%	15.03%	3.57%
High School Graduate	35.08%	32.24%	2.83%
Some College or College Graduate	46.59%	45.21%	1.38%
Child in HH (age <19)	47.58%	47.49%	0.09%
Employed	71.58%	71.43%	0.15%
Working < 20 hours per week	4.58%	3.93%	0.66%
Working >= 20 hours per week	66.99%	67.50%	0.51%
Working 20-35 hours per week	9.98%	9.74%	0.24%
Working >= 35 hours per week	57.01%	57.75%	0.74%
% Unemployed	3.30%	3.77%	0.47%
% earning <= 200% of the FPL	30.45%	27.82%	2.64%
% on Official Poverty	11.76%	11.23%	0.53%
Self Reported Health Status	2.20	2.22	0.02

Notes: The table reports summary statistics using the CPS data after using the person-level sample weights (health weights are used for the health insurance variables). The sample is restricted to adults in Oklahoma and the South Region from 2000 to 2005, ages 19-64, and not in the armed forces. The IPUMS defined South Region includes Maryland , North Carolina, South Carolina, Virginia, West Virginia, Delaware, Florida, Georgia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas. The first column lists the variable of interest. The second column includes the percent in Oklahoma. The third column includes the percent in the South Region. The final column, Difference, displays the absolute value of the percent difference between Oklahoma and the South Region.

Table 3.2: CPS DD Regressions Results

	(1)	(2)	(3)	(4)	(5)	(6)
ESHI = Employer Sponsored Private Health Insurance	Employed with ESHI	Has Private Health Insurance	Has Public Health Insurance	Employment	Self Reported Health Status	Emergency Room Visits per 1000 people
OKlahoma x Post 2005	0.0372***	0.0310***	0.0054	0.0018	0.0685***	54.6167***
Stnd Errors Clustered at the State Level	(0.0037)	(0.0048)	(0.0033)	(0.0028)	(0.0120)	(4.9673)
R^2	0.9147	0.9040	0.8660	0.8762	0.9181	0.9580
Mean of Dependent Variable	0.5142	0.6378	0.1354	0.7013	2.2924	450.4438
Percent Change From Mean	0.0724	0.0486	0.0400	0.0026	0.0299	0.1213

*** p<0.01, ** p<0.05, * p<0.1

Notes: The sample uses the CPS data and includes Oklahoma and the states in the South Region as defined by IPUMS between 2000 and 2009 using the health insurance weights for the health insurance variables and person-level sample weights for the other three variables. Each column depicts results running the difference-in-difference regression equation (1) with the dependent variable as shown in the top row. The individual level data is collapsed to the state-by-year aggregate level to run the regressions after eliminating everyone in the armed forces and outside of the ages [19, 64). The sample consists of means for each state (resulting in 160 observations: 16 states over 10 years). State fixed effects and year fixed effects are included but not shown. Standard errors are calculated by clustering at the state level.

Appendix to Chapter 1

Electricity Abbreviations

AECT	Association of Electric Companies in Texas
COOP	Cooperative
ERCOT	Electric Reliability Council of Texas
FERC	Federal Energy Regulatory Commission
IOU	Investor Owned Utility
ISO	Independent System Operator
kWh	kilowatt-hour
MOU	Municipally Owned Utility
NERC	North American Electric Reliability Corporation
PUC	Public Utility Commission
SERC	Southeastern Electric Reliability Council
SPP	Southwest Power Pool
TCAP	Texas Coalition for Affordable Power
TRE	Texas Reliability Entity
WECC	Western Electric Coordinating Council

A.1. Background (Detailed)

Beginning in the 1890's, electric utilities took advantage of economies of scale and emerged in urban areas (Centerpoint, 2014). In 1907, the first state regulated electricity markets began, and by 1920 two-thirds of the states regulated their electricity markets (Centerpoint, 2014). In 1935, after the Great Depression revealed that the companies in the electricity market were over hedged and state regulation had proven incapable of controlling the actions of interstate holding companies headquartered out of state, Congress passed the Federal Power Act and Public Utility Holding Company Act (Centerpoint, 2014). [93] The former controls interstate sales of electricity while the latter enables federal regulation of the corporate structure of the utility (Centerpoint, 2014). Over the next 40 years, federal regulation strengthened.

[93] See http://www.purdue.edu/discoverypark/energy/assets/pdfs/History.pdf for more information.

The electricity market in the United States began changing in the late 1970's as the desirability of using regulated vertically integrated units to control all aspects of electricity came into question. In 1978, with the passage of the Public Utility Regulatory Act, deregulation began. It strengthened in 1992 when the Federal Energy Regulatory Commission (FERC), responsible for interstate electricity trading, unbundled sales and transportation services.[94] In 1995, Texas' Senate Bill 373 created wholesale competition within the Electric Reliability Council of Texas (ERCOT) as, among many things, it required utilities to provide independent generators with nondiscriminatory open access to their transmission lines to support wholesale competition in ERCOT (PUC, 2104). In 1996, FERC issued Order 888 which effectively did the same thing as Senate Bill 373 for the United States (TCAP, 2012). These events set states into motion deregulating their electricity market.

In the United States, the electricity markets are under the jurisdiction of the North American Electric Reliability Corporation (NERC) which is subject to the FERC (which regulates interstate trading). FERC and NERC overlap when the entire region is within the United States. The electric systems in Texas fall under four separate reliability regions of the NERC, the: Western Electric Coordinating Council (WECC), Texas Reliability Entity (TRE), Southwest Power Pool (SPP), and Southeastern Electric Reliability Council (SERC) (AECT, 2014). ERCOT, which makes up the entire TRE region, is an independent system operator (ISO) that manages about 90% of the state's electric load, 43,000 miles of transmission lines, and 550 generation units (ERCOT,

[94] See http://www.energyilluminated.com/history_of_energy_deregulation for more information.

2014). In general, ERCOT does not fall under FERC jurisdiction since ERCOT is entirely within Texas. The other 10% of the state's load falls under the following ISOs; the WECC, SPP, and Midcontinent ISO. Further, these ISOs fall under jurisdiction of the FERC since they also encompass other states. Finally, each of the ISOs in Texas falls under jurisdiction of the state regulator, which has oversight from the Texas Legislature (PUC, 2014). See Figure A.1 for a depiction of the NERC regions, Figure A.2 for the ISO's in Texas, and Figure A.3 for FERC's division of power markets. See AECT, ERCOT, FERC, or PUC (2014) for more information.

Prior to 1995, regulated utility markets were typically vertically integrated entities controlling all four areas of electricity: generation, transmission, distribution, and retail. Generation entails producing the electricity. Transmission moves the electricity from the generating facility to local communities and connects regions. Distribution disperses it within the local community to the house or business. Finally, retail involves the utility's interface with the end-user, providing hookup, metering, and billing services.

Three types of companies operate electricity markets in Texas; Municipally Owned Utilities (MOUs), Cooperatives (COOPs), and Investor Owned Utilities (IOUs). MOUs and COOPs were regulated by the state regulator up until the early 1990's when they became deregulated. However, they kept their status of having only one supplier of electricity to the region they operated in. The bigger MOUs and COOPs (e.g. Austin, San Antonio, and Pedernales) are vertically integrated utility companies controlling all four areas of electricity but not regulated by the state regulator. Smaller MOUs and COOPs do not own generation, transmission, or distribution and thus only buy electricity from generators or electricity providers. The majority of the electricity in Texas is monitored and controlled by ERCOT and thus many MOUs and COOPs fall under ERCOT's jurisdiction. Those that do not (about 10% of them) are controlled by the WECC, SPP, and SERC. No matter their size, electricity market they own, or jurisdiction they fall under, all MOUs and COOPs within Texas have one firm providing electricity to the people in the region in which they operate and are not regulated by the state regulator.

Prior to 2002, all IOUs in Texas were regulated by the state regulator. Senate Bill 7, passed in 1999, required the retail electricity market for all the IOUs within ERCOT to open to competition by 2002—it allowed retail electric providers to buy electricity from generators or owners of electricity and sell it to industrial, commercial, and residential customers in the deregulated IOU regions (TCAP, 2012). Therefore, after January 2002, all IOUs within ERCOT were deregulated. All MOUs and COOPs, and other IOUs in Texas but outside of ERCOT, were not directly affected by Senate Bill 7. The MOUs or COOPs have kept their same status since the early 1990s. The IOUs outside of ERCOT have kept their same status even longer.

A.2. Economic Theory for Regulation and Deregulation

The main reason for regulating electricity markets has been to take advantage of economies of scale. Transmission and Distribution requires power lines (large capital investments) to move electricity from the power plant to the end users. Once in place, the marginal costs of getting power to the customer are trivial, but the upfront costs are very high--similar to a modern cable company. In these settings, average total cost decreases as output increases. It has generally been accepted that one company providing this entire service enables lower costs because they can take advantage of the economies of scale by purchasing and providing the network required to move the electricity from generation to household. Since capitalist economies do not promote monopoly existence as they allow the producer to supply lower quantities at higher prices compared to competitive markets (which increases producer surplus, decreases consumer surplus, and creates deadweight loss) we either regulate them or allow the government to operate them. The regulation or actual ownership by the government of this natural monopoly prevents private companies from taking advantage of its market power (a market failure) and charging exorbitant prices.

Figure A.4 helps explain why markets are regulated and what proponents hoped to achieve through deregulation. Markets produce where marginal revenue = marginal costs (MR=MC). In a competitive market, firms are price takers. They can produce any quantity they want and earn the MR equal to the market price. They produce where MR is equal to their MC, which at an aggregate level happens at point C. In the competitive market, firms produce Q_c at price P_c. Consumer surplus equals the area of triangle CDE, producer surplus equals the area above the MC curve and below line CE, and there is no deadweight loss. For a monopolist, MR = MC at point B (in contrast to firms in a competitive market, monopolists determine the price). A monopolist produces Q_m at price P_m. Consumer surplus equals the area of triangle MFD, producer surplus equals the area above the MC curve and below line FM, and deadweight loss equals the area of triangle CBM. The monopolist produces a lower quantity at a higher price than a competitive market, takes some of the consumer surplus, and also creates a deadweight loss (which is the source of the inefficiency in the market).

The monopolist is regulated in order to try and move his quantity closer to Q_c and prices closer to Pc to minimize the deadweight loss. For many reasons beyond the scope of this paper, the regulator aims to make the regulated price between P_m and P_c, typically a little markup above what the regulator determines P_c is. Thus, in many markets, moving from an unregulated monopolist to a regulated one decreases prices as does moving from a regulated monopolist to a deregulated, competitive market. In theory this is what should happen, but in practice it does not always happen, as explained and shown in this paper. As the price decreases from P_m, the quantity increases and the deadweight loss decreases.

Regulation has potential drawbacks. Regulating a monopoly reduces their incentives to keep costs down and to pursue efficiencies in operations. Under traditionally regulated systems, utilities have a financial incentive to build out their systems to the largest extent possible (without regard to efficiency) and then request repayment of these costs through increased tariffs (known as advance cost recovery) to increase their overall profits (TCAP, 2012).[95] The end consumer bears the burden of these large, risky capital investments, investments a private company are less likely to make.

[95] See http://www.scpolicycouncil.org/research/taxes/energy-deregulation for an explanation of advanced cost recovery.

Due to the economy of scale issue, the electricity market has a clear place where private markets and government regulated or controlled markets can co-exist. In electricity markets, generation and retail customer service can be competitive while the wire business (transmission and distribution) can remain a natural monopoly (Newbury, 1999). Opening up the generation and retail customer service to private markets while keeping the transmission and distribution regulated enables electricity market's to enjoy the fruits of competition and the economies of scale gained from transporting the electricity.

Many economists think opening the market to competition has many advantages. In general, the thought is that competition fosters efficiency and lowers prices. Newbury gives many benefits (1999). He describes how "competition is more effective than regulation at cutting costs to improve efficiency, and aligning prices with costs to improve allocative efficiency." Regulators are caught between the inevitable tension that comes from keeping prices low between incentives improving efficiency and the credibility of the commitment not to steal those efficiency gains from the company as they share the responsibility for protecting both consumers and the utility. Further, as Newbury writes, "competition provides stronger and less manipulable incentives to efficiency than regulation." Additionally, moving from regulation to competition avoids a main problem noted in Stigler's paper that regulation is acquired by the industry and is designed and operated primarily for its benefit (1971). This section demonstrates that many economists prefer a deregulated, competitive industry – which is exactly what Senate Bill 7 mandated.

A.3. WHY THE PRICE OF NATURAL GAS AFFECTS THE CONTROLS DIFFERENTLY

Four investor owned utility companies were not deregulated by Senate Bill 7. These four include: El Paso Electric, Entergy, Southwestern Electric Power, and Southwestern Public Service. These companies were not forced to deregulate because they were not contained entirely within Texas and thus the Texas state legislature did not have the authority to deregulate them. Since they are not entirely contained within Texas, these four companies use a different electricity operator than the deregulated regions. They procure the bulk of the electricity for their customers from their electricity operator. Due to using a different electricity operator, they use a different mix of fuels (which may include less natural gas) to produce electricity than companies that operate entirely within Texas. Therefore, when the price of natural gas changes, since they use less natural gas for electricity production than the five regions deregulated, the effects from it have a smaller impact. Further, the total costs to these regulated companies entails more than just fuels which dampens the impact from the price of natural gas even further.

El Paso Electric falls under FERC's Southwest Electric Region and NERC's WECC Region. Entergy falls under FERC's SERC and Midcontinent region and NERC's SERC Region. Southwestern Electric Power and Southwestern Public Service fall under FERC's SPP Region which corresponds to NERC's SPP Region.[96] The primary fuel used in the Southwest, TRE, and SPP region is natural gas while it is coal in the SERC and MISO region (FERC, 2015). All of these regions use coal for their

[96] See Figure A3 for a pictorial representation.

baseload fuel (EIA, 2015). Southwest, TRE, and SPP use natural gas to supplement anything over baseload. SPP, SERC, and MISO mainly supplement with coal.

Cooperatives also follow average cost pricing. These entities are not-for-profit. Thus, they need to cover costs but do not want to earn profits. By charging based on average costs, they ensure they cover their costs without earning profits. If they were to charge based on marginal costs and marginal costs were higher (lower) than average costs they would earn positive (negative) profits. Marginal cost pricing can lead to the commonly referred to “missing money” problem detailed in William Hogan, 2005. Earning profits and not covering costs both entail their own problems. To avoid these problems, cooperatives charge based on average costs.

Many municipalities, like the companies in the deregulated regions, maximize profits. They use the electricity market profits for other municipal expenses (Austin Energy and City of San Antonio, 2015). For example, Austin Energy hopes to make a large enough profit to cover about $150 million that the city takes for municipal expenses from their profits (Duncan, 2015). Since there are no direct competitors though, they do not follow the standard Bertrand model. They do, indirectly, have many competitors. Since municipalities (and cooperatives) can opt-in to competition at any time, they have to ensure their prices are competitive enough that their voting base does not vote to opt-in. Thus, they keep a close watch on the prices of electricity in the deregulated markets and ensure they are competitive with those. Like firms in deregulated regions, the municipalities maximizing profits base prices off marginal cost pricing and at the same time they stay competitive with deregulated rates to avoid being “opted-in.” Specifically, Austin Energy has a goal of being in the bottom 50% of the electricity prices of companies in Texas (Guermouche, 2015). Further, they set mandates on the amount of renewables that must be used to produce electricity for their customers. These goals and mandates are set by its city council who acts like a board of directors for a competitive firm. All municipalities are overseen by a similar type of board, though it may not be a city council. The few municipalities that operate as non-profits follow average cost pricing as described in the prior paragraph explaining cooperative's pricing methods.

To understand the way Texas charges for electricity in the state, an example may help. A typical day in Texas might entail a max demand of 37.5 GW (Webber, 2015). In 2012, the max demand in Texas was 66.8 GW which occurred on Aug 7 (a very hot day when air conditioning is vital) and the minimum demand was 23.3 GW which occurred on April 1 (middle of the night when little electricity is used and a household does not need to heat or cool their house) (Webber, 2015). With a price of $0.68/MBTU for nuclear, $1.88/MBTU for coal (the most expensive seen from 1994 to 2012 for both of these), and $3.35/MBTU for natural gas (by far the cheapest seen from 2002 to 2011), the highest bid that will be accepted/needed is the natural gas power plant that bids $28.70/MWh (Webber, 2015). Therefore, the wind and solar generators that bid less than $1/MWh, the nuclear plants that bid close to $12.29/MWh, the coal plants that bid close to $26.07/MWh, and the cheaper natural gas plants that bid close to $27.93/MBTU are all used and receive the market clearing price of $28.70/MWh. Any firm buying electricity in the day-ahead or real-time market pays $28.70/MWh. Since the deregulated firms use these two markets more, they are more at the mercy of the price of natural gas. For natural gas not to be the primary driver of the generation plants to be used the demand of electricity or the price of natural gas must be very low. The demand would need to be below 30 GW (seen about 10% of the time) or the price would need to be lower than prices seen between 2000 to 2011 (Webber, 2015).

Companies entering into longer bilateral contracts will not have their costs fluctuate as much as companies entering into 1 to 3 year contracts. Given that 5-20% of the electricity purchased is in the day-ahead or real-time market, while current fuel costs will affect a firm's total costs and thus prices charged to residential customers, it will affect a firm's costs much less if most of their electricity is already fixed. The biggest difference from the different durations will be that a company with a fixed contract for 1 year will have to renegotiate their costs and update their prices annually while the company with a 10, 15, or even 30-year contracts will renegotiate and update much less frequently, possibly missing the entire time period over which the price of natural gas fluctuated so drastically.

One other point concerning one COOP/IOU should be disclosed.[97] Cap Rock Electric Cooperative changed to Cap Rock Energy Corporation on Sept 1, 2003. By making this change, they changed their status from a cooperative to an independently owned investor utility. Despite being entirely within Texas' boundaries (within NERC's and FERC's TRE region), the state regulator regulated them after determining they were

[97] The information in this paragraph comes from reading the historic files on the PUC website located at: http://interchange.puc.texas.gov/WebApp/Interchange/application/dbapps/filings/pgSearch.asp

not large enough to foster adequate competition.[98] They planned to deregulate this region after competition sufficiently built up in the five deregulated regions. On July 13, 2010, Sharyland Utilities bought Cap Rock Energy Corporation and the state regulator continued to regulate them. In 2014, past the date of my data, this region was deregulated. The regression results presented in this paper categorized Cap Rock as the EIA reported them – as a COOP to 2003 and then as a regulated IOU. Regression results without Cap Rock in the data are available upon request. Results are almost identical to the results presented in the paper.

A.4. Non-Weighted Results, Support for Quantity being Exogenous, Balanced Panel Set

In section A.4.1, I provide non-weighted graphs and non-weighted estimates for the two main figures and tables presented in the main analysis. Due to not weighting the regressions, the figures and coefficients in these tables actually represent: How did deregulation affect the average price producers charge? In section A.4.2, I provide justification for why quantity can be considered exogenous in the electricity market. In section A.4.3, I present results using equations (1) and (4) on a balanced panel data set.

A.4.1. Non-Weighted Regression Results

Figure A.5 depicts a parallel trend prior to 2002 and a break in prices after 2002 between the deregulated and control regions. Figure A.5 is very similar to Figure 1.3, the weighted version, with the one exception that the break does not happen until 2005, almost three years following deregulation. Upon further reflection, this makes sense. In

[98] This region had 22,000 customers in 2002 and 26,000 in 2012 (almost 0.22% of total customers).

the initial years following deregulation, many firms entered the market and charged low prices to try and attract new customers. Many of these firms charged such low prices and could not attract enough customers that they eventually went out of business. After two or three years of many failed attempts, entering firms learned how to price in the market and how to better attract customers. Due to the initial low prices charged by firms who went out of business, the price producers charged in the deregulated regions are lower than the prices customers were actually paying. Figure A.2 captures this difference.

Table A.1 presents non-weighted regression estimates of equation (1). It is identical in structure and format to Table 1.2. For the same reason as specified in the *Empirical Analysis* section, column (3) is the preferred specification. β is similar to the weighted regression estimate – though it is smaller. From 2002-2006, deregulation caused the price producers charged to increase by \$9/month. δ is quite different. It is smaller in magnitude, negative, and only significant at the 10% level. $\beta + \delta$ is significant at better than the 1% level and is about 25% the size of $\beta + \delta$ in the weighted regression. From 2007-2012, deregulation caused the price producers charged to increase by \$7/month. The average price charged by producers is still greater in the deregulated regions compared to the controls, but it is much less than the price the average consumer paid. This difference suggests that customers in deregulated regions were staying with higher priced firms.

Figure A.6 follows the same format as Figure 1.7. It depicts the difference in the average prices (as opposed to Figure 1.7 which depicts the weighted average prices) between the deregulated and control regions and the price of natural gas. It is similar to

Figure 1.7 with the one exception being the same one noted and explained when describing Figure A.1—the break in prices does not seem to happen until 2005.

Table A.2 presents non-weighted regression estimates of equation (4). It is identical in structure and format to Table 1.3. For the same reasons as before, column 3 is the preferred specification. Inspecting the triple interaction terms, one can see that from 2002 to 2006, a $1/MBTU in the price of natural gas leads to a $3.26/month increase in the price producers charge. From 2007 on, this increases to $5.28/month (and is statistically significant at greater than the 1% level). While β_2 is similar, $\beta_2 + \delta_2$ is almost twice as much in the non-weighted regression compared to the weighted one. Using the same logic as explained earlier, one can calculate that, from 2002 to 2006, deregulation leads to producers charging lower prices if the price of natural gas creeps below $2.46/MBTU. From 2007 on, this value changes to $3.40/MBTU. Figure 5 shows that, while the price of natural gas was not below $2.46/MBTU from 2002 to 2006, it was below $3.40/MBTU in 2012. In 2012, the price of natural gas was $2.93/MBTU. Therefore, while deregulation led to producers charging more money overall, in 2012, it actually led to producers charging less money. The phenomenon is demonstrated in Figures A.5 and A.6 in 2012, where the average price charged by producers in deregulated regions is less than the average price charged by producers in the control regions.

Due to the consumer inertia problem, this difference between weighted and non-weighted graphs and regressions makes sense. The weighted ones take into account that most people stay with the more expensive incumbent instead of switching to lower cost options. Thus, the results in the weighted regressions will be higher compared to the non-weighted ones as the non-weighted ones treat every producer the same and do not take into account how many people they actually had paying their prices. Clearly, customers could have made themselves better off, from a financial perspective, switching from the incumbent to lower cost alternatives. Further analysis using some of the cheaper priced firms might reveal that customers could in fact have saved money following deregulation—had they chosen to take the time and effort to search out cheaper options and make the switch.

A.4.2. Quantity is Arguably Exogenous

Figure A.7 depicts average quantity sold for the deregulated and control regions. Quantity sold is on the vertical axis and year is on the horizontal axis. Following 2002 and 2007, there do not appear to be any clear breaks between the trends for the deregulated and control regions.

Table A.3 depicts regression results from equation (1a).

$$\ln(q_{jtr}) = \alpha_0 + \alpha_r + \alpha_t + \beta * D_{jr} * \boldsymbol{I}_{t\geq 2002} + \delta * D_{jr} * \boldsymbol{I}_{t\geq 2007} + \varepsilon_{jtr} \quad (1a)$$

$ln(q_{jtr})$ equals the natural log of the quantity of electricity sold by firm j at time t in region r. The table and specifications are structured similar to Table 1.2. Regression results show there do not appear to be any significant impacts from deregulation. No matter the specification used, β is insignificant, both economically and statistically. While δ is statistically significant at the 5% or 1% level, the values are always economically insignificant. The largest value of δ shows a 0.075% decrease. Removal of a price floor should have either no effect or allow firms to charge lower prices which would cause an increase in quantity. The negative value of δ, combined with its low economic significance and statistical insignificance of β, support that quantity is arguably exogenous to prices. Further, $\beta + \delta$ is statistically and economically insignificant in every specification. This analysis shows that, over the 11 years following deregulation, people do not alter their use of electricity based on prices (usage is highly inelastic). While column (4) in Tables 1.2 and 1.3 were not used as the main specification, this analysis supports quantity is exogenous and demonstrates column (4) from those tables could have been used as the preferred specification (though results between columns 3 and 4 in Tables 1.2 and 1.3 are nearly identical in size and significance).

A.4.3. Using a Balanced Panel Data Set

Tables A.4 and A.5 recreate Tables 1.2 and 1.3 but use a balanced panel data set. In order to balance the panel, I eliminated 2 municipalities, 22 cooperatives, and 4 investor owned utilities. These 28 companies either exited the data before 2012 or did not enter until after 1994. They created the unbalanced panel that I used for my main analysis. Importantly, there is no predictable pattern of an entering or exiting strategy and only 1 of these 28 companies exited in 2001, just prior to deregulation. Therefore, the entry and exit decisions of these firms do not seem to relate to deregulation.

After eliminating the 28 companies, the number of regions decreases from 163 to 135. The number of observations decreases from 3,196 to 2,950. Table A.4 presents resulting running equation (1) with this balanced panel. Table A.5 presents results running equation (4) with this balanced panel. Coefficients and significance in both tables are almost exactly as they are in the main analysis presented in the paper.

A.5. ALLOWING THE EFFECT OF DEREGULATION TO VARY BY YEAR

The second half of the paper dealt with the cost of natural gas having a differential effect on the residential electricity prices in deregulated regions versus control regions. As shown above, as the cost of natural gas increased, the difference the customers in the deregulated regions paid increased. Another hypothesis might be that each year has a different effect. Perhaps, as time evolves prices between the treated and control regions separate or converge. In order to test the effect by year, I run a difference-in-difference regression that takes the following form:

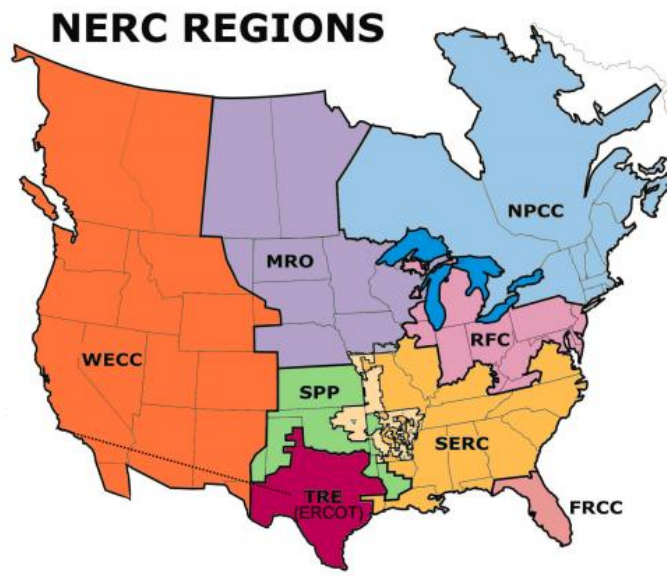
$$p_{jtr} = \alpha_0 + \alpha_r + \alpha_t + \sum_{t=1994}^{t=2012} \beta_t * D_{jr} * \alpha_t + \varepsilon_{jtr}. \quad (1a)$$

All subscripts, variables, and parameters have the same meaning as they did in equation (1). The difference between (1a) and (1) is that instead of the interaction of deregulation with a post 2002 and post 2007 dummy, deregulation is interacted with an indicator for every year. Results are displayed in appendix Table A.6.

The format of Table A.6 follows the same format as prior tables, with the variable of interest listed on the far left hand side and each column corresponding to some form of equation (1a) being run (the columns follow the same format as Table 1.2). Although the estimate includes all deregulation-by-year interactions for all years in my sample (1994 to 2012), I only display the coefficients for the post-deregulation years (2002 to 2012) for brevity. Looking at column (3), the preferred specification, one can see that there is a gradual increase on the monthly amount the average customer in the deregulated region pays relative to the average customer in the control regions through 2006. From 2007 on, the coefficients are all significant at the 1% level, are always positive, and, in general, begin to decrease (with the one exception being 2009 is greater than 2008). The decrease starting in 2007 lines up with the removal of the price floor in which incumbents were no longer restricted to a price they could not charge below.

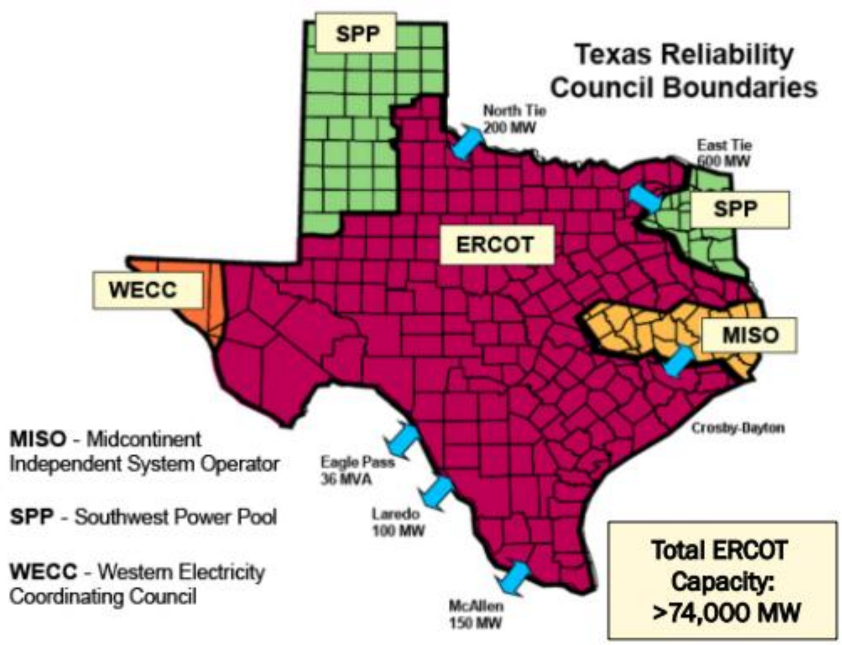
All point estimates show the customers in deregulated regions paid a greater price than customers in the control regions except for in 2002. This anomaly makes sense considering the information given in the *Background* section that prices were initially set in the deregulated regions at 6% less than 1999 levels. Clearly, the years 2006 through 2009 had the greatest difference in what customers in control versus deregulated regions were paying. While it might be that deregulation took time to actually make an impact, these years roughly line up with the years that the cost of natural gas was at its highest (from 2005 to 2008, refer to Figure 1.5). The magnitude of all the coefficients line up closely with the pattern we see in the cost of natural gas. Given all the above information, the effect from deregulation when looking at it by year follows the exact same pattern we expect to see. Running the regression in this manner supports this paper's conclusion that the cost of natural gas affects the deregulated and control regions differently and that the deregulated regions will pay a higher price when the cost of natural gas increases.

Figure A.1: NERC Regions in North America



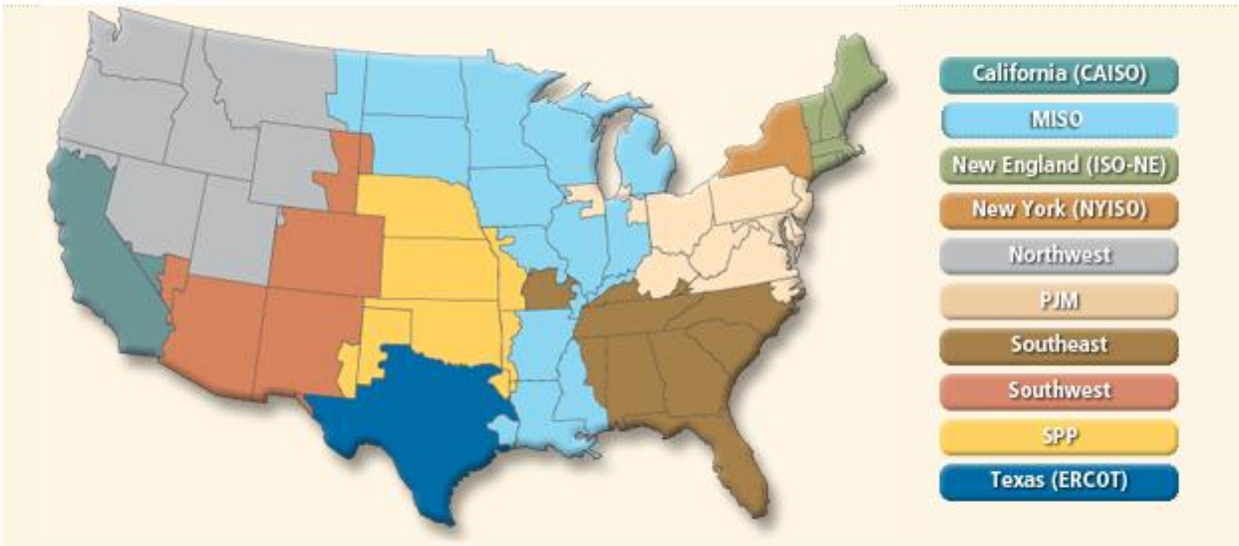
Notes: The shaded areas in the figure above depict the different regions of the North American Electric Reliability Corporation. Source: AECT, 2014.

Figure A.2: Independent System Operators in Texas



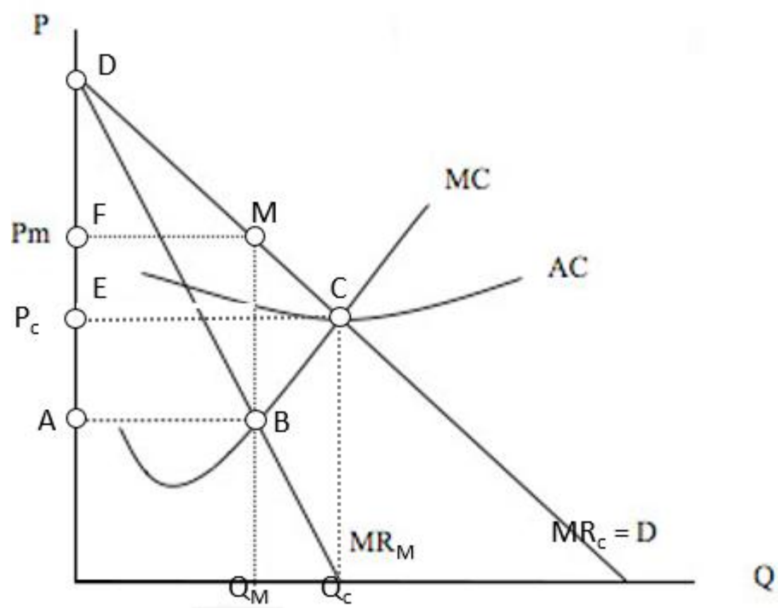
Notes: The shaded areas in the figure above depict the different independent system operators in Texas. Source: AECT, 2014.

Figure A.3: FERC division of power markets



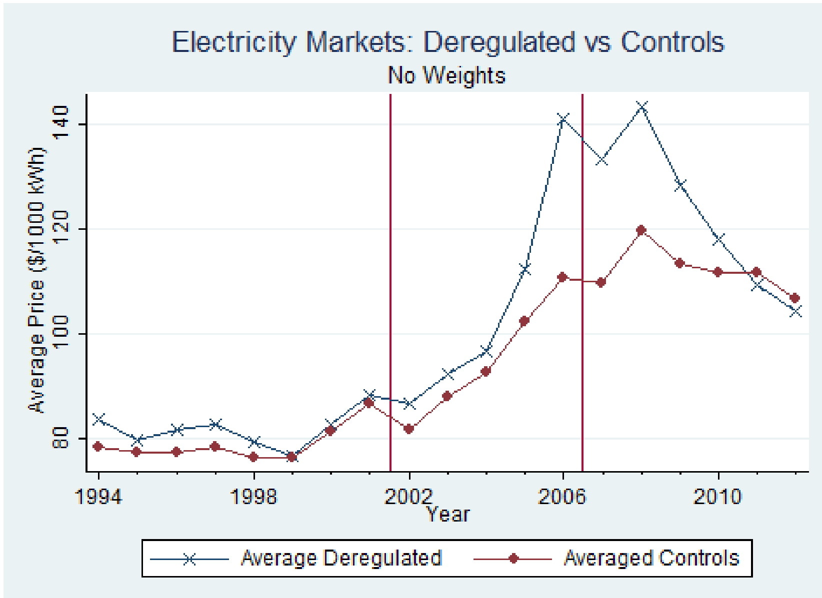
Notes: The shaded areas in the figure above depict the Federal Energy Regulatory Commission's division of market powers in the United States. Source: www.ferc.gov.

Figure A.4: Monopoly vs Competitive Market



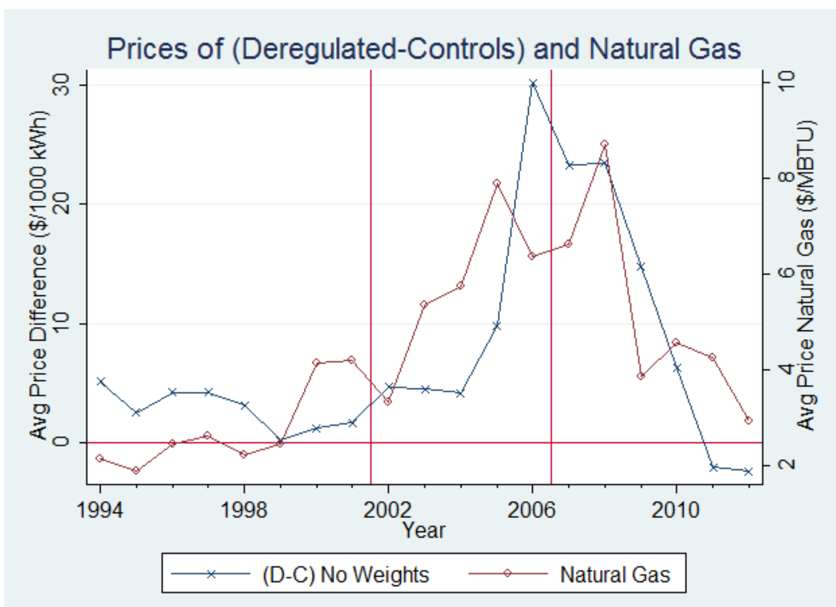
Notes: The figure above illustrates a standard model to show price and quantity effects when being in a competitive market, monopoly market, and a regulated one. Price is on the y-axis and quantity is on the x-axis. See text for details.

Figure A.5: Average Price of Deregulated Regions vs Controls



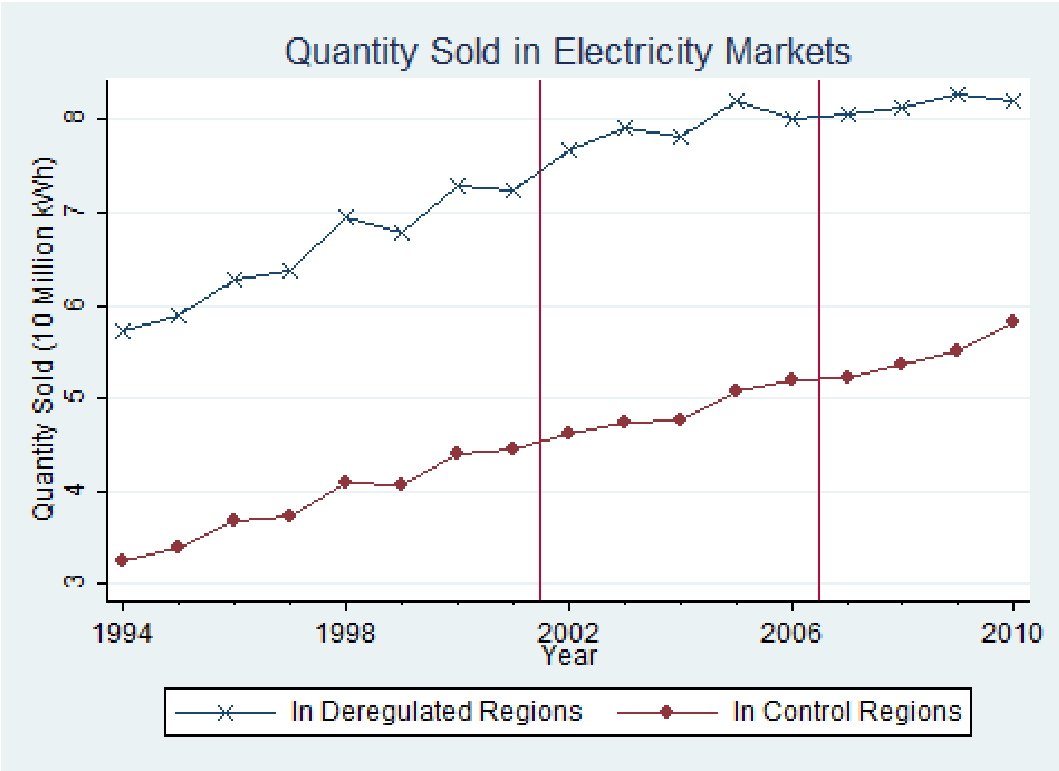
Notes: The figure above depicts, each year, the average price of the deregulated and control firms. See Figure 1.3 notes for more details.

Figure A.6: Price of (Deregulated– Controls Firms) and the Price of Natural Gas



Notes: This figure depicts the average price difference between the deregulated and control regions (on the left hand side vertical axis) and the average price of natural gas (on the right hand side vertical axis). See Figure 1.3 notes for more details.

Figure A.7: Quantity Sold in the Deregulated and Control Regions



Notes: The figure above depicts, each year, the quantity of electricity sold in the deregulated regions and the control regions. Quantity sold, in 10 million kWh, is on the y-axis and year is on the x-axis. See Figure 1.3 notes for more details.

Table A.1: Dependent Variable: Average Price ($/1,000 kWh)

Regression Results Not Weighted				
VARIABLES	(1)	(2)	(3)	(4)
	Using all regulated and deregulated firms			
Dereg * I_{2002}	11.022***	8.955***	9.011***	13.872***
	(0.842)	(0.881)	(0.804)	(0.859)
Dereg * I_{2007}	-5.384***	-2.084*	-2.064*	-1.843
	(0.885)	(1.117)	(1.160)	(1.160)
Dereg	2.865***	2.841***		
	(0.969)	(0.972)		
I_{2002}	16.012***			
	(0.842)			
I_{2007}	17.380***			
	(0.885)			
Observations	3,196	3,196	3,196	3,196
R-squared	0.395	0.483	0.749	0.754
Controls	None	None	None	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes
Mean of Dependent Variable = 96.37 (0.427)				

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors in () are clustered at the region level (163 regions, 1 treated). Format is identical to Table 1.2. The controls in column (4) are quantity of electricity sold and the number of customers. This table uses all the deregulated firms and all the controls from 1994 to 2012.

Table A.2: Dependent Variable: Average Price ($/1,000 kWh)

Non-Weighted Regression Results				
VARIABLES	(1)	(2)	(3)	(4)
	Using all regulated and deregulated firms			
Dereg * I_{2002}	2.677*	-8.218***	-8.027***	3.533
	(1.421)	(2.247)	(1.952)	(2.957)
Dereg * I_{2007}	-12.794***	-9.970***	-9.929***	-8.809***
	(1.974)	(2.033)	(2.049)	(2.082)
Dereg	-3.999***	5.455***		
	(0.969)	(1.464)		
I_{2002}	-15.542***			
	(1.421)			
I_{2007}	41.122***			
	(1.974)			
PNG*Dereg * I_{2002}	-0.192	3.375***	3.261***	1.217*
	(0.252)	(0.529)	(0.480)	(0.682)
PNG*Dereg * I_{2007}	2.415***	2.017***	2.018***	1.860***
	(0.272)	(0.275)	(0.275)	(0.282)
PNG* Dereg	2.472***	-0.942**	-0.773*	1.372**
	(0.000)	(0.456)	(0.408)	(0.618)
PNG*I_{2002}	5.487***			
	(0.252)			
PNG*I_{2007}	-4.014***			
	(0.272)			
Observations	3,196	3,196	3,196	3,196
R-squared	0.452	0.491	0.758	0.762
Controls	None	None	None	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	None	Yes	Yes
Mean of Dependent Variable = 96.37 (0.427)				

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors in () are clustered at the region level (163 regions, 1 treated). Format is identical to Table 1.3. The controls in column (4) are quantity of electricity sold and the number of customers. This table uses all the deregulated firms and all the controls from 1994 to 2012.

Table A.3: Dependent Variable: ln (total sales)

VARIABLES	1	2	3
Dereg * I_{2002}	0.538	0.539	0.031
	(0.437)	(0.438)	(0.031)
Dereg * I_{2007}	-0.075***	-0.075***	-0.059**
	(0.027)	(0.027)	(0.023)
I_{2002}	0.117*		
	(0.069)		
I_{2007}	0.105***		
	(0.025)		
Dereg	4.265***	4.265***	
	(0.627)	(0.628)	
Observations	2,583	2,583	2,583
R-squared	0.197	0.199	0.993
Controls	None	None	None
Year Fixed Effects	No	Yes	Yes
Region Fixed Effects	No	No	Yes

*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors in () are clustered at the region level (163 regions, 5 treated). By combining data sets I am able to obtain quantity per firm per region for the deregulated firms and thus can keep the five deregulated regions separate in the pre and post time periods. Each column provides more independent variables as indicated in the bottom of the table. This table uses all the deregulated firms and all the controls from 1994 to 2010.

Table A.4: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results Using Balanced Panel				
VARIABLES	1	2	3	4
	Using all regulated and deregulated firms			
Dereg * I_{2002}	14.334***	14.334***	14.726***	14.584***
	(1.055)	(1.039)	(1.070)	(1.067)
Dereg * I_{2007}	9.006***	9.006***	9.131***	8.635***
	(1.369)	(1.385)	(1.373)	(1.361)
Dereg	7.711***	7.711***		
	(2.747)	(2.752)		
I_{2002}	13.574***			
	(1.055)			
I_{2007}	12.817***			
	(1.369)			
Observations	2,950	2,950	2,950	2,950
R-squared	0.619	0.749	0.858	0.858
Controls	None	None	None	Quantity
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes
Mean of Dependent Variable, weighted = 96.38 (3.61)				

*** p<0.01, ** p<0.05, * p<0.1

Notes: Robust standard errors in () are clustered at the region level (135 regions, 1 treated). Asterisks next to the coefficients are for p-values calculated using robust clustered standard errors. This table uses the years 1994 to 2012 and eliminates the control companies as necessary to create a balanced panel of data. The table follows the same format as Table 1.2. See text for more details.

Table A.5: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results Using Balanced Panel				
VARIABLES	(1)	(2)	(3)	(4)
	Using all regulated and deregulated firms			
Dereg * I_{2002}	-7.333***	-15.763***	-15.334***	-14.422***
	(2.211)	(2.074)	(2.212)	(2.125)
Dereg * I_{2007}	24.645***	24.645***	25.089***	25.465***
	(2.791)	(2.799)	(2.776)	(2.814)
Dereg	-2.120	6.311**		
	(2.749)	(3.032)		
I_{2002}	-14.134***			
	(2.211)			
I_{2007}	33.876***			
	(2.791)			
PNG*Dereg * I_{2002}	1.933***	4.970***	4.900***	4.641***
	(0.498)	(0.426)	(0.455)	(0.436)
PNG*Dereg * I_{2007}	-2.403***	-2.403***	-2.458***	-2.642***
	(0.307)	(0.307)	(0.311)	(0.325)
PNG* Dereg	3.541***	0.504	0.628	1.818***
	(0.000)	(0.378)	(0.404)	(0.587)
PNG*I_{2002}	4.815***			
	(0.498)			
PNG*I_{2007}	-3.528***			
	(0.307)			
Observations	2,950	2,950	2,950	2,950
R-squared	0.703	0.761	0.870	0.871
Controls	None	None	None	Quantity
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes
Mean of Dependent Variable, weighted = 96.38 (3.61)				

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Robust standard errors in () are clustered at the region level (135 regions, 1 treated). Asterisks next to the coefficients are for p-values calculated using robust clustered standard errors. This table follows the same format as Table 1.3. See Table 1.3 and appendix Table A.4 for more details.

Table A.6: Dependent Variable: Average Price ($/1,000 kWh)

Weighted Regression Results				
VARIABLES	1	2	3	4
Dereg * $I_{t=2002}$	-24.222***	-5.665***	-5.676***	-5.738***
	(1.039)	(1.665)	(1.688)	(1.690)
Dereg * $I_{t=2003}$	-10.201***	1.055	1.149	1.040
	(1.039)	(1.943)	(1.960)	(1.966)
Dereg * $I_{t=2004}$	-2.606**	5.475***	5.605***	5.466***
	(1.039)	(0.928)	(0.914)	(0.917)
Dereg * $I_{t=2005}$	11.663***	11.349***	11.562***	11.350***
	(1.039)	(0.989)	(1.002)	(1.002)
Dereg * $I_{t=2006}$	40.069***	33.978***	34.217***	33.924***
	(1.039)	(2.116)	(2.163)	(2.153)
Dereg * $I_{t=2007}$	21.375***	30.508***	30.737***	30.391***
	(1.702)	(1.717)	(1.722)	(1.713)
Dereg * $I_{t=2008}$	25.872***	24.295***	24.520***	24.160***
	(1.702)	(1.864)	(1.871)	(1.866)
Dereg * $I_{t=2009}$	21.606***	29.047***	29.290***	28.897***
	(1.702)	(2.258)	(2.302)	(2.305)
Dereg * $I_{t=2010}$	7.927***	15.592***	15.850***	15.431***
	(1.702)	(2.497)	(2.557)	(2.564)
Dereg * $I_{t=2011}$	-1.698	4.865***	5.159***	4.706***
	(1.702)	(1.683)	(1.726)	(1.743)
Dereg * $I_{t=2012}$	-2.479	6.125**	6.311**	5.786**
	(1.702)	(2.381)	(2.466)	(2.482)
Dereg	18.570***	12.272***		
	(2.638)	(3.003)		
$I_{t\geq2002}$	13.647***			
	(1.039)			
$I_{t\geq2006}$	12.832***			
	(1.328)			
Observations	3,196	3,196	3,196	3,196
R-squared	0.760	0.782	0.891	0.891
Controls	None	None	None	Quantity
Year Fixed Effects	No	Yes	Yes	Yes
Region Fixed Effects	No	No	Yes	Yes
Mean of Dependent Variable, weighted = 96.43 (3.60)				

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Robust standard errors in () are clustered at the region level (163 regions, 1 treated). Asterisks next to the coefficients are for p-values calculated using robust clustered standard errors. Although the estimate includes all deregulation-by-year interactions for all the years in my sample, I display coefficients for the post-deregulation years (2002-2012) above for brevity. The table follows the same format as Table 1.2 and A.4 except that it uses equation (1a) which interacts the year with deregulation to allow for the treatment effect of deregulation to vary by year in a nonparametric way.

References

FOR CHAPTER 1

(AECT). Association of Electric Companies in Texas, 2014. "Electricity 101: Operations and Recent Statistics." Accessed 15 Sept to 5 Dec 2014 at: www.aect.net/library/electricity-101.

Apt, J., 2005. "Competition Has Not Lowered U.S. Industrial Electricity Prices." The Electricity Journal 18 (2), 52–61.

Austin Energy. Interviews with Employees in the Generation, Estimation, and Retail Sections of the Company. Jan-Apr 2015.

Axelrod, H., DeRamus, D., Cain, C., 2006. "The Fallacy of High Prices." Public Utilities Fortnightly 144 (11), 55–60.

Basheda, G.N., J.P. Pfeifenberger, A.C. Schumacher, 2007. "Restructuring Revisited." Public Utilities Fortnightly. Accessed 22 Sept 2015 at: www.fortnightly.com

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics*, 119 (1): 249-275.

Borenstein, S. and Holland, S. "On the Efficiency of Competitive Electricity Markets With Time-Invariant Retail Prices." *RAND Journal of Economics*, Vol. 36 (2005), pp. 469–493.

Centerpoint Electric, 2014. "Electricity 101." Edison Electric Institute. Accessed 20 Nov 2014 at: http://www.centerpointelectric.com/staticfiles/CNP/Common/SiteAssets/doc/EEI%20 Electricity_101.pdf.

City of San Antonio. Interviews with employees in the Generation, Estimation, and Retail sections of the company. Jan-Apr 2015.

Conley Timothy G. and Christopher Taber, 2011. "Inference with 'Difference in Differences' with a Small Number of Policy Changes." *The Review of Economics and Statistics*, 93 (1): 113-125.

Davis, Lucas W. and Erich Muehlegger, 2010. "Do Americans Consume Too Little Natural Gas? An Empirical Test of Marginal Cost Pricing." *RAND Journal of Economics*, 41 (4): 791–810.

DEFG, 2012. "Texas Electricity Market Design Most Successful in North America." News and Media Press Releases, December 2012. Accessed 22 Sept 2015 at: http://defgllc.com/news/article/texas-electricity-market-design-most-successful-in-north-america/

Klump, 2015. "Texas Garners Top Spot in Residential Choice as 8 States Decline." DEFG, News and Media Press Releases, July 2015. Accessed 2 Oct 2015 at: http://defgllc.com/news/article/texas-garners-top-spot-in-residential-choice-as-8-states-see-decline/

Donald, Stephen G. nd Kevin Lang. 2007. "Inference with Difference-in-Differences and Other Panel Data." The Review of Economics and Statistics. 89 (2): 221-233.

Duncan, Robert. Personal Interview. Former President of Austin Energy. 2015.
(EIA). Energy Information Administration. Data sources obtained from 15 Sept to 15 Dec 2014 at: http://www.eia.gov/electricity/sales_revenue_price/index.cfm for sales, revenue, average price, and number of customers; http://www.eia.gov/electricity/state/texas/ for generation and price information; http://www.eia.gov/tools/faqs/faq.cfm?id=97&t=3 for household use per month

(ERCOT). "About ERCOT." Accessed 15 Sept to 5 Dec 2014 at http://www.ercot.com.

(FERC). Federal Energy Regulatory Commission. Accessed 27 March 2015 at http://www.ferc.gov/market-oversight/mkt-electric/overview.asp.

Fagan, Mark L. 2006. "Measuring and Explaining Electricity Price Changes in Restructured States." Harvard University JFK School of Government, RPP-2006-02.

Giulietti, Monica, Catherine Price, and Michael Waterson, 2005. "Consumer Choice and Competition Policy: A Study of UK Energy Markets." Economic Journal 115 (506): 949–68.

Griffin, James M. and Steven L. Puller, 2005. Electricity Deregulation: Choices and Challenges. *"A Primer on Electricity and the Economics of Deregulation*," Chicago: University of Chicago Press, Draft.

Guermouche, Sid. Current employer Austin Energy. 2015

Hogan, William. 2013. "Electricity Scarcity Pricing Through Operating Reserves." Economics of Energy and Environmental Policy. V2, Number 2.

Hogan, William. September 23, 2005. "On an 'Energy Only' Electricity Market Design for Resource Adequacy." Unpublished.

Hortaçsu, Ali, Seyed Ali Madanizadeh, and Steven L. Puller, 2012. "Power to Choose? An Analysis of Choice Frictions in the Residential Electricity Market." Unpublished.

Ito, Koichiro, 2012. "Do Consumers Respond to Marginal or Average Price? Evidence from Nonlinear Electricity Pricing." Unpublished.

Joskow, P.L., 2006. "Markets for Power in the United States: an Interim Assessment." The Energy Journal 27 (1), 1–36.

Joskow, Paul, and Jean Tirole, 2006. "Retail Electricity Competition." RAND.

Joskow, Paul L., and Catherine D. Wolfram, 2012. "Dynamic Pricing of Electricity." American Economic Review 102 (3): 381–85.

Kang, L. and Zarnikau, J., 2009. "Did the expiration of retail price caps affect prices in the restructured Texas electricity market?" Energy Policy 37, 1713–1717.

Mahoney, Neale, and E. Glen Weyl. 2014. "Imperfect Competition in Selection Markets." *NBER Working Paper.*

Nakajima, T. and Hamori, S., 2010. "Change in consumer sensitivity to electricity prices in response to retail deregulation: A panel empirical analysis of the residential demand for electricity in the United States." Energy Policy 38, 2470–2476.

Newbury, David, 1999. Privatization. Restructuring, and Regulation of Network Utilities. Chapter 5: "Introducing Competition into Network Utilities."

Puller, Steven L., and Jeremy West, 2013. "Efficient Retail Pricing in Electricity and Natural Gas Markets." American Economic Review, 103(3): 350-55.

Puller, Steven L., 2007. "Pricing and Firm Conduct in California's Deregulated Electricity Market," Review of Economics and Statistics, February 89(1): 75-87.

(PUC). Public Utility Commission of Texas. http://www.puc.texas.gov accessed 15 Sept to 5 Dec 2014. Specific sights accessed follow: http://www.puc.texas.gov/industry/electric/reports/scope/2003/2003scope_elec.pdf, https://www.puc.texas.gov/agency/topic_files/101/PUC-History_Dereg_ERCOT.pdf,

https://www.puc.texas.gov/industry/maps/maps/tdumap.pdf,
For 4 parts of electricity and information on generation deregulation:
http://www.puc.texas.gov/industry/electric/reports/scope/1997/1997vlscop_elect.pdf

Roe, B., Teisl, M., Levy, A., Russel, M., 2001. “U.S. consumers’ willingness to pay for green electricity.” Energy Policy 29, 917–925.

Rose, K., 2004. “The state of retail electricity markets in the U.S.” The Electricity Journal 17 (1), 26–36.

Stigler, George J, 1971. “The Theory of Economic Regulation,” The Bell Journal of Economics and Management Science, Vol. 2 (1), pp. 3-21.

Swadley, Adam and Yucel, M., 2011. “Did residential electricity rates fall after retail competition? A dynamic panel analysis.” Energy Policy 39, 7702–7711.

Su, Xuejuan. 2015. “Have Customers Benefited From Electricity Retail Competition?” Journal of Regulatory Economics 47, 146-182.

(TCAP). Texas Coalition for Affordable Power, 2012. “Deregulated Electricity in Texas: A History of Retail Competition.”

Webber, Michael, 2015. Energy 101: Energy Technology and Policy, UT Austin, accessed online 4 March 2015 at www.enegy101.com.

Webber, Michael, 2015. Lecture Notes. *Electricity Sector I and II.*

Whitworth, D. and Zarnikau, J., 2006. “Has electric utility restructuring led to lower electricity prices for residential consumers in Texas?” Energy Policy 34 (15), 2191–2200.

Woo, C.K., Zarnikau, J., 2009. “Will electricity market reform likely reduce retail rates?” The Electricity Journal 22 2, 40–45.

Zarnikau, J., et al., Trends in Prices to Commercial Energy Consumers in the Competitive Texas Electricity Market. Energy Policy (2007), doi:10.1016/j.enpol.2007.02.024

Zummo, Paul, 2015. “2014 Retail Electric Rates in Deregulated and Regulated States,” American Public Power Association. Accessed 22 September 2015 at:
https://www.publicpower.org/files/PDFs/2015RetailRatesReportFinal.pdf

For Chapter 2

Aizer, Anna and Jeffrey Grogger, 2003. "Parental Medicaid Expansions and Health Insurance Coverage." NBER Working Paper # 9907, August.

Azuara, Oliver. and Ioana Marinescu, 2011. "Informality and the Expansion of Social Protection Programs," Working Paper, MPRA Paper 35073, Munich, University Library of Munich.

Baicker, K, A. Finkelstein, J. Song, S. Taubman, 2013. "The Impact of Medicaid on Labor Force Activity And Program Participation: Evidence from the Oregon Health Insurance Experiment," NBER Working Paper 19547.

Baicker, Katherine, Sarah Taubman, Heidi Allen, Mira Bernstein, Jonathan Gruber, Joseph Newhouse, Eric Schneider, Bill Wright, Alan Zaslavsky and Amy Finkelstein, 2013. "The Oregon Experiment – The Effect of Medicaid on Clinical Outcomes," *New England Journal of Medicine*, 368: 1713-1722.

Barker, Ryan. Vice President of Health Policy, *Missouri Foundation for Health*, Personal Interviews: 2013 and 2014.

Barros, Rodrigo. 2008. "Wealthier but Not Much Healthier: Effects of a Health Insurance Program for the Poor in Mexico", mimeo, Standford University.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics*, 119(1): 249-275.

Bitler, Marianne. Jonah Gelbach, and Hilary Hoynes, 2006. "What Mean Impacts Miss: Distributional Effects of Welfare Reform Experiments." *The American Economic Review*, 96(4): 988-1012.

Burke, Mary A, 2014. "Rhode Island in the Great Recession: Factors Contributing to its Sharp Downturn and Slow Recovery," Current Policy Perspectives, Federal Reserve Bank of Boston; 14-9.

Campos-Vazquez R. and M. Knox, 2013. "Social Protection Programs and Employment: The Case of Mexico's Seguro Popular Program," *Economia Mexicana*, V XXII, num.2.

Card, David and Lara Shore-Sheppard, 2004. "Using Discontinuous Eligibility Rules to Identify the Effects of the Federal Medicaid Expansions on Low Income Children." *Review of Economics and Statistics* 86 (3), 752–766.

Chase, Deborah, L. Kemper, W. Peck, 2008. “Effects of the 2005 Missouri Medicaid Legislation on Recipients: Measuring Changes in Coverage, Care, and Health Status,” Health Policy Publication, Missouri Foundation for Health.

Currie, Janet and Brigitte Madrian, 1999. “Health, Health Insurance and the Labor Market,” in O. Ashenfelter and D. Card (ed.), Handbook of Labor Economics, 1(3): 3309-3416.

Dhaval, Dave, Sandra Decker, Robert Kaestner, Kosali Simon, 2013. “The Effect of Medicaid Expansions in the Late 1980s and Early 1990s on the Labor Supply of Pregnant Women,” NBER Working Paper 19161.

Decker, S. L. and F. W. Selck, 2012. “The Effect of the Original Introduction of Medicaid on Welfare Participation and Female Labor Supply.” *Review of Economics of the Household*, 10(4): 541-556.

Dubay, Lisa and Genevieve Kenney, 1996. “Effects of Medicaid Expansions on Coverage of Children.” *Future of Children* 6 (1), 152–161.

Dubay, Lisa and Genevieve Kenney, 1997. “Did Medicaid Expansions for Pregnant Women Crowd-out Private Insurance?” *Health Affairs* 16 (1), 185–193

Ferber, J, J Frost, C. Goldstein, A. Smoucha, and K. Warren, 2005. “The 2005 Missouri Medicaid Cuts: A Guide for Consumers, Families, and Advocates.”

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and the Oregon Health Study Group, 2012. “The Oregon Health Insurance Experiment: Evidence from the First Year.” *Quarterly Journal of Economics*, 127(3).

Gruber, Jonathan, 2000. “Health Insurance and the Labor Market.” In Culyer, A. J. and Newhouse, J. P., editors, Handbook of Health Economics, pages 645–706. Elsevier Science.

Gruber, Jonathan and Brigitte Madrian, 2004. “Health Insurance, Labor Supply, and Job Mobility: A Critical Review,” in Catherine McLaughlin ed. Health Policy and the Uninsured, Washington, D.C.: Urban University Press: 97-178.

Gruber, Jonathan and Kosali Simon, 2008. “Crowd Out 10 Years Later: Have Recent Public Insurance Expansions Crowded Out Private Health Insurance?” *Journal of Health Economics*, 27: 201:217.

Garthwaite, C. and T. Gross, M. Notowidigdo, 2014. “Public Health Insurance, Labor Supply, and Employment Lock,” *The Quarterly Journal of Economics*, 129(2): 653-696.

Ham, Jon and Lara Shore-Sheppard, 2005. “The Effect of Medicaid Expansions for Low-income Children on Medicaid Participation and Private Insurance Coverage: Evidence from the SIPP.” *Journal of Public Economics* 89, 57–83.

LoSasso, Anthony T. and Thomas Buchmueller, 2004. “The Effect of the State Children's Health Insurance Program on Health Insurance Coverage.” *Journal of Health Economics* 23, 1059–1082.

Medicaid.gov. Accessed online on 11 June, 2015 at: http://medicaid.gov/affordablecareact/provisions/eligibility.html

Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2010.

Missouri Foundation for Health (MFH). Personal Interviews: 2013 and 2014 with Ryan Barker.

Missouri Senate. Accessed online on 26 June, 2015 at: http://www.senate.mo.gov/05info/BTS_Web/Actions.aspx?SessionType=R&BillID=22520.

Notowidigdo, Matthew J. Neubauer Family Assistant Professor of Economics, Personal Interviews: 5 Dec 2013 and multiple in 2014.

Oklahoma Health Care Authority, Annual Reports “Then & Now.” Accessed online on 5 February, 2015 at http://www.okhca.org.

Rao J.N.K. and Jeff Wu, 1988. “Resampling Inference with Complex Survey Data,” *Journal of American Statistical Association*, 83 (401): 231-241.

Shore-Sheppard, Lara D., 2005. “Stemming the Tide? The Effect of Expanding Medicaid Eligibility on Health Insurance.” NBER Working Paper 11091.

Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2010.

Strumpf, E., 2011. “Medicaid's Effect on Single Women's Labor Supply: Evidence From the Introduction of Medicaid.” *Journal of Health Economics,* 30 (3): 531–548.

Thorpe, K., Florence, C., 1998. “Health Insurance Coverage Among Children: the Role of Expanded Medicaid Coverage.” Inquiry 35 (4), 369–379.

U.S. Census Bureau. Accessed online on 8 June, 2015 at: http://www.infoplease.com/us/census/data/missouri/ and http://quickfacts.census.gov/qfd/ and choose Oregon or Missouri for demographic information.

U.S. Department of Health and Human Services (USDHHS). Accessed online on 8 June, 2015 at: http://aspe.hhs.gov/poverty/05poverty.shtml.

Wong, Michelle, Tay McNamara, Sandee Shulkin, Chelsea Lettieri, and Vanessa Careiro, 2008. “Rhode Island Indicators: Aging and Work,” *The Center on Aging and Work, State Perspectives,* Boston College, State Profile Series; accessed 16 September 2015 at: www.bc.edu/agingandwork

Yazici, Esel and Robert Kaestner, 2000. “Medicaid Expansions and the Crowding Out of Private Health Insurance Among Children.” Inquiry 37 (1) (Spring), 23–32.

Yelowitz, Aaron, 1995. “The Medicaid Notch, Labor Supply, and Welfare Participation: Evidence from Eligibility Expansions,” *The Quarterly Journal of Economics,* 110(4): 909-39.

Zuckerman, Stephen, Dawn Miller and Emily Shelton Paper, 2009. “Missouri's 2005 Medicaid Cuts: How Did They Affect Enrollees and Providers,” *Health Affairs*, 28(2): w335-w345.

FOR CHAPTER 3

Affordable Care Act: Accessed 1 July 2015 at: http://kff.org/health-reform/fact-sheet/summary-of-the-affordable-care-act/.

Anderson, Michael, Carlos Dobkin, and Tal Gross, 2014. “The Effect of Health Insurance on Emergency Department Visits: Evidence from an Age-Based Eligibility Threshold,” *Review of Economics and Statistics,* 96(1): 189-195.

Azuara, Oliver. and Ioana Marinescu, 2011. “Informality and the Expansion of Social Protection Programs,” Working Paper, MPRA Paper 35073, Munich, University Library of Munich.

Baicker, K, A. Finkelstein, J. Song, S. Taubman, 2013. "The Impact of Medicaid on Labor Force Activity And Program Participation: Evidence from the Oregon Health Insurance Experiment," NBER Working Paper 19547.

Baicker, Katherine, Sarah Taubman, Heidi Allen, Mira Bernstein, Jonathan Gruber, Joseph Newhouse, Eric Schneider, Bill Wright, Alan Zaslavsky and Amy Finkelstein, 2013. "The Oregon Experiment – The Effect of Medicaid on Clinical Outcomes," *New England Journal of Medicine*, 368: 1713-1722.

Baldwin, L. M, E. H. Larson, F. A. Connell, D. Nordlund, K. C. Cain, M. L. Cawthon, P. Byrns, R. A. Rosenblatt, 1998. "The Effect of Expanding Medicaid Prenatal Services on Birth Outcomes." *American Journal of Public Health*, 88(11)): 1623–1629. Print.

Barros, Rodrigo. 2008. "Wealthier but Not Much Healthier: Effects of a Health Insurance Program for the Poor in Mexico", mimeo, Standford University.

Campos-Vazquez R. and M. Knox, 2013. "Social Protection Programs and Employment: The Case of Mexico's Seguro Popular Program," *Economia Mexicana*, V XXII, num.2.

Coey, Dominic, 2015. "The Effect of Medicaid on Health Care Consumption of Young Adults." *Health Econ*omics, 24(5): 558–565.

Decker, S. L. and F. W. Selck, 2012. "The Effect of the Original Introduction of Medicaid on Welfare Participation and Female Labor Supply." *Review of Economics of the Household*, 10(4): 541-556.

Dubay, Lisa and Genevieve Kenney, 1997. "Did Medicaid Expansions for Pregnant Women Crowd-out Private Insurance?" *Health Affairs* 16 (1), 185–193

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, Katherine Baicker, and the Oregon Health Study Group, 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year." *Quarterly Journal of Economics*, 127(3).

Gruber, Jonathan, 2000. "Health Insurance and the Labor Market." In Culyer, A. J. and Newhouse, J. P., editors, Handbook of Health Economics, pages 645–706. Elsevier Science.

Gruber, Jonathan and Brigitte Madrian, 2004. "Health Insurance, Labor Supply, and Job Mobility: A Critical Review," in Catherine McLaughlin ed. Health Policy and the Uninsured, Washington, D.C.: Urban University Press: 97-178.

Gruber, Jonathan and Kosali Simon, 2008. "Crowd Out 10 Years Later: Have Recent Public Insurance Expansions Crowded Out Private Health Insurance?" *Journal of Health Economics*, 27: 201:217.

Garthwaite, C. and T. Gross, M. Notowidigdo, 2014. "Public Health Insurance, Labor Supply, and Employment Lock," *The Quarterly Journal of Economics*, 129(2): 653-696.

Ham, Jon and Lara Shore-Sheppard, 2005. "The Effect of Medicaid Expansions for Low-income Children on Medicaid Participation and Private Insurance Coverage: Evidence from the SIPP." *Journal of Public Economics* 89, 57–83.

Miriam King, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick. Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2010.

Notowidigdo, Matthew J. Neubauer Family Assistant Professor of Economics, Personal Interviews: 5 Dec 2013 and multiple in 2014.

Oklahoma Health Care Authority, Annual Reports "Then & Now." Accessed online on 5 February, 2015 at http://www.okhca.org.

Oklahoma Health Care Authority. Accessed 1 July 2015 at: http://www.okhca.org/research.aspx?id=9662&parts=7447.

Oklahoma Policy Institute (2010). "Tobacco Taxes." OKPolicy.org. Accessed 16 September 2015 at: okpolicy.org/files/tobacco_2010.pdf?635234.

Shore-Sheppard, Lara D., 2005. "Stemming the Tide? The Effect of Expanding Medicaid Eligibility on Health Insurance." NBER Working Paper 11091.

Steven Ruggles, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder, and Matthew Sobek. Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor], 2010.

Strumpf, E., 2011. "Medicaid's Effect on Single Women's Labor Supply: Evidence From the Introduction of Medicaid." *Journal of Health Economics*, 30 (3): 531–548.

Taubman, Sara, Heidi Allen, Bill Wright, Katherine Baicker, Amy Finkelstein, 2014. "Medicaid Increases Emergency-Department Use: Evidence from Oregon's Health

Insurance Experiment," *Science*, 343: 263-268.*The American Economic Review*, 96(4): 988-1012.

U.S. Census Bureau. Accessed online on 8 June, 2015 at: http://www.infoplease.com/us/census/data/oklahoma/.

Yelowitz, Aaron, 1995. "The Medicaid Notch, Labor Supply, and Welfare Participation: Evidence from Eligibility Expansions," *The Quarterly Journal of Economics*, 110(4): 909-39.